Mobility tools holding and intermodality modelling in Paris

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Mobility tools holding and intermodality modelling in Paris

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English abstract

To fulfil mobility needs, individuals make trips involving an access to mobility systems granted by mobility tools such as vehicles, subscriptions to mobility services and license holding. The strategical choice of mobility tools portfolio composition determines the mode choice universe for trip making: large portfolios enable using and mixing several modes and can generate an intermodal trip alternative for trip makers. In order to improve the understanding of mobility, this dissertation investigates strategical and tactical trip making choices and their interaction by analysing the mobility tools holding and intermodality phenomena. Before a potential integration of these mobility phenomena into metropolitan mobility models, two main questions arise: what is the magnitude and what are the characteristics of each phenomenon, and how does it interact with the mobility structure? Answering these goes through conceptualizing, qualifying and modelling the two study mobility phenomena. This research aims on providing answers to these elements within the metropolitan mobility travel demand modelling field framework. Literature review, modelling for mobility planning, discrete choice, statistical, geographic and socio-economic tools are employed on a household travel survey dataset to support the analyses.
The thesis begins with a brief review of mobility concepts and data sources involved, before focusing on a disaggregated metropolitan approach with the study of the Paris region and the one individual households study population. The thematic and methodological backgrounds are described before addressing the strategical mobility tools holding choice including seven tools: driving license, car, car parking space, motorcycle, bike, PT pass subscription and bike sharing subscription. The dissertation ends with a study of the tactical trip making choice focusing on intermodality demand, and questions its relationship with the previous mobility tools holding phenomenon.
Main results include the set-up of a metropolitan mobility model characterization framework, a conceptualization of the mobility tools holding phenomenon, a mobility tools holding structure hierarchy, an evidence of the interest of jointly modelling mobility tools holding, a characterization of intermodal trips and users and an exploratory modelling of intermodality demand.

Keywords: Transport planning; Mobility demand modelling; Mobility tools holding; Portfolio modelling; Intermodality; Statistical analysis of mobility; Paris case study.

Abstract en français

En réponse aux besoins de mobilité, les individus réalisent des déplacements via des équipements de mobilités (i.e. véhicules, abonnements à des services de mobilités et licences). Le choix stratégique du portefeuille d'équipements de mobilité détermine l'univers des alternatives pour le choix du mode lors d'un déplacement : des portefeuilles variés permettent l'utilisation et la combinaison de plusieurs modes générant des alternatives intermodales. Pour améliorer la compréhension de la mobilité, cette thèse étudie les choix stratégique et tactique de détention d'équipements de mobilité et d'intermodalité respectivement, ainsi que leur interaction. Envisager la représentation de ces phénomènes au sein des modèles de mobilité métropolitaine soulève deux interrogations: quel est l'ordre de grandeur et quelles sont les caractéristiques de chaque phénomène, et comment interviennent-ils dans la structure du choix de mobilité ? Répondre à ces questions mène à conceptualiser, qualifier et modéliser ces deux phénomènes au sein du domaine de la modélisation de le demande de mobilité métropolitaine. La modélisation comme outil de planification, des modèles de choix discrets, des analyses statistique, géographique et socio-économique sont appliqués à une enquête ménage-déplacements pour étudier ces phénomènes.

Cette dissertation débute par une revue de concepts clés et de sources de données de mobilité, avant d'adopter une approche désagrégée appliquée à la région parisienne et plus particulièrement à la population des ménages à un individu. Les contextes thématique et méthodologique sont exposés, puis le phénomène de détention de sept équipements de mobilité (permis de conduire, automobile, parking, motocycle, vélo, abonnement aux transports en commun, abonnement au service de vélos partagés) est étudié. Une analyse du choix tactique de mode de déplacement se concentrant sur l'intermodalité en interaction avec le précédent choix d'équipements de mobilité vient conclure cette thèse.

Les principaux résultats incluent la construction d'un cadre d'analyse des modèles de mobilité, la conceptualisation de la détention d'équipements de mobilité, la hiérarchisation de ces équipements, un exemple de l'intérêt de modéliser simultanément plusieurs équipements, une caractérisation des trajets et des individus intermodaux, et une modélisation exploratoire de la demande en intermodalité.

Mots clés : Planification des transports; Modélisation de la demande de mobilité; Détention d'équipements de mobilité; Modélisation de panoplie d'équipements; Intermodalité; Analyses statistiques de la mobilité; Cas d'étude francilien.

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Introduction

Background

With more than 50% of the world population and a 2% annual growth rate, urban areas are quickly growing all over the world according to UN Habitat (2016). Mobility is a key element of the metropolitan system and plays a critical role in the local economic, social and environmental development. While an efficient metropolitan mobility system favours the movement of goods and people fostering cultural exchanges and trade opportunities, the transport sector is also responsible for 25% of the world CO_2 emissions in 2017 according to the IEA (2019), and forecasts from the ITF (2019) estimate that these emissions will grow by 60% between 2015 and 2050. Understanding metropolitan mobility and its evolution is key for managing world sustainable development challenges.

Going into more detail, a metropolitan area is a complex geographical system where several areas with different densities, land-use characteristics and constraints are gathered within the same spatial entity. Metropolitan mobility is an answer to the complex local activity demand and supply, connecting the different elements of this system in order to facilitate exchanges and provide added value through combined connection effects. Dupuy et al. (2008) provides elements illustrating that the relationship between metropolitan development and mobility supply development is the engine of urban growth. The metropolitan mobility development is currently driven by societal and technological developments such as the emergence of teleworking, of sustainable development concern, of smartphone diffusion, information systems and automation technologies. This evolving environment has contributed to increasing the connectivity of each individual and the need for a higher connection to more people and goods. These developments have led to changes regarding the way mobility tools are held: from a traditional Public Transit (PT) ticket and car holding equilibrium, several mobility services have been developed all over the world in the early XXIst century. These services enable mobility tools subscription possibilities instead of traditional ownership. The initial enthusiasm for private motorized motorized modes is also fading for a renewed interest for active and collective modes. Another behavioural evolution relates to how individuals move on a network. When there used to be a need for planning monomodal trips on fixed origin and destination points, the increased interconnection of mobility networks indirectly resulting from the development of mobility services enables more versatile behaviours combining several modes to make intermodal trips. All these trends contribute to an increase of alternatives for the mobility tools holding and trip making mode choices, triggering an interrogation on the relationship between mobility tools holding and use, and between individual and collective mobility.

The societal and technological mobility evolution also has some impact on mobility modelling representation. Indeed, while mobility planning used to be dedicated to forecasting flows linked with new PT or car infrastructures, it must now account for environmental impacts and especially GreenHouse Gases (GHG) emissions, socio-economic inequalities reduction associated with car, PT and other available private vehicles and mobility services. These changes are fostered by an extended modal diversity and the need to promote active modes questions the base planning theories historically developed for managing car and rail infrastructure investments, which should evolve to account for this new mobility setting.

With a more technical and methodological perspective, these changes modify the way individual mobility choices are made and their time frame. They challenge the historical aggregated approach behind the four step travel demand models and highlight the need to expand or transform models to better account for the wide set of phenomena affecting the mobility choices. For instance, while it was easy to differentiate vehicle ownership on a long-term strategical temporal scale from vehicle use within the mode choice on a short-term tactical temporal scale, the subscription possibilities add another intermediate temporal scale blurring the former segmented temporal decision frame.

Research question

In order to account for the growth of mobility services related with evolving vehicle ownership behaviours, for a higher modal diversity and for potential trips made through mode combinations, this dissertation deals with the representation of modal diversity in urban mobility planning models at the mobility tools holding and intermodal trip making level. It involves providing detailed analyses and modelling specifications of these phenomena in the Paris region, and interrogating the definition, the descriptors and the modelling approaches of the two study phenomena.

Accounting for mobility tools holding introduced by Scott & Axhausen (2006); Le Vine (2011) is a shift from traditional transport modelling perspectives often considering the car and PT accessibility of a household or an individual as an input of the model instead of directly representing it as a mobility phenomenon. These initial models made sense when considering that trip making generally is a much more immediate choice on a very short time frame, while owning a vehicle is a longer-term decision. But that assumption is less true with the increased modal diversity and the possibility to quickly subscribe and cancel a subscription to a mobility service. Conceptually, considering that mobility tools holding is an input of mobility models is also inaccurate as this amounts to considering that an individual or a household does not purchase vehicles or subscribe to mobility services based on the trips that it is expecting to make. Including this phenomenon in the mobility representation process is a logical modelling evolution highlighted in Trouve & Leurent (2018).

But mobility tools holding also is a complex phenomenon because it involves several types of mobility tools that are held on different time scales, that have different durability features according to Cernicchiaro (2013), that give access to different transport networks, and that are not always held on an individual basis only but also within a broader household strategy as suggested by Astroza et al. (2018). A questioning of the mobility tools holding concept is necessary to better assess it. Aside questioning the concept, the identification of the characteristics explaining the phenomenon is important to address too. More explicitly, it involves establishing which are the main individual socio-economic and geographic characteristics summarized through quantified indicators that best explain mobility tools holding. The question of the mobility tools combination effects for the same individual or household is also relevant and could reveal combination patterns.

This diversity of modes and mobility tools is likely to support a wider practice of intermodal trips combining at least two different transport modes within the same trip. This challenges again traditional models considering a mode choice alternative among a fixed number of modes, without potential interactions between them. Focusing on this intermodality phenomenon leads to investigating what a mode is, for which modal combination a trip is considered intermodal, what are the determinants of intermodal individuals and uses. It also enables highlighting the interactions among individual characteristics, mobility tools holding and mobility uses.

These phenomena related to the field of applied mobility research can be described by a systemic socio-economic analysis on a specific geographic frame, to get a general perspective combining the effects of several explanatory factors. As such, it involves perspectives from several research fields, making it an interdisciplinary research question. This interdisciplinary perspective involves a large panel of methods from which some specific ones should be selected to best fit the study phenomena. A piece of the answer to dealing with the issue of the potential representation of individual behaviours on a metropolitan scale goes through questioning which of these methods bring knowledge on the phenomena, to select tools tailored to the analysed phenomena.

To sum up, the objectives in this study are to interrogate, depict and estimate the mobility tools holding and intermodality phenomena on a real metropolitan area study case, with methods coming from the interdisciplinary mobility analysis applied research field.

Objectives

The aforementioned questions are answered by defining a set of objectives:

– *Understand the mobility tools holding and intermodality phenomena* by reviewing existing literature and statistically analysing phenomena patterns and individual holding and use behaviours based on socio-economic and geographic descriptive variables. It involves identifying relevant methods for displaying meaningful results. It also includes differentiating the descriptors of each mobility tools from the descriptors of combined mobility tools within a portfolio, including the previous separate mobility tools descriptors plus mobility tools combination effects. Regarding intermodality, this objective also encompasses the analysis of intermodal trips characteristics.

– *Estimate mobility tools holding on the one hand, and intermodal usage on the other hand, as individual choices* by statistically modelling holding rates and the intermodality mode share. The aim of this estimation process is not to provide forecasts but to observe and interpret the values of model parameters and their meaning regarding their related descriptive variable. It enables to test candidate choice structures and segmentations of the choice population, and to confirm results of the first descriptive statistical analysis on an applied statistical exercise.

– *Highlight the interaction between mobility tools holding and trip making* by integrating trip characteristics in the statistical analysis of mobility tools holding, and by reciprocally considering mobility tools holding portfolios in the analysis of the mode choice structure including intermodality. This objective focuses on the dual causality that strategic mobility tools holding and tactical mode choice behaviours have on each other, with an application to commuter trips. The focus on these trips is justified by the strong trip constraints which are expected to play a role in and be influenced by mobility tools portfolio choice.

– *Apply the modelling methods to a field case: the Paris region* to work with real observations from the EGT 2010 household travel survey dataset. This metropolitan area displayed a significant improvement of its mobility system with the emerging bike sharing Vélib' mobility service in 2010, and a set of local incentives aiming to favour bike, collective transport and intermodal trip making. This strategy to move away from the traditional car and public transit equilibrium with a higher modal diversity makes the Paris region a relevant field for studying mobility tools holding and generates higher inter-modality possibilities. This objective more generally involves understanding the specificities of the field to get a better overview of the analysis results and to discuss their potential generalisation.

Research topic overview

The mobility demand field of research has mostly grown since the 1950s, with the development of a systemic approach to transport in interaction with spatial characteristics in Voorhees (1959), the development of the discrete choice theory with McFadden (1974); Ben-Akiva & Lerman (1985) enabling to represent the mode choice process, and the use of route choice optimisation procedures such as presented in Leurent (2006). These elements have been gathered into a wider mobility modelling theory by Bonnel (2004); Wegener (2004); Ortùzar & Willumsen (2011) based on the interaction among land-use, trip generation, trip distribution, mode choice, trip assignment processes, and now often with an additional transport emission process. As the major developments of the mobility demand field happened in the the second half of the XXth century, the analyses generally are oriented on a road versus PT network equilibrium.

Within this research field, the studies addressing mobility tools holding and intermodality are recent and distinct, probably because those fields are not sufficiently developed yet.

First, the mobility tools holding field has begun with the study of car ownership as a consumption good in Cramer (1959); Trognon (1978). Some modelling attempts to combine the consumption of several goods such as in Lancaster (1966); Rault (1969); Ashford & Sowden (1970), but with a theoretical approach not often applied on study cases. More detailed models of private car ownership have been developed and summed up in de Jong et al. (2004a); Anowar et al. (2014a), but without considering the interaction with other mobility tools. Other models have been built considering separate mobility tools such as Nagai et al. (2003); Hsu et al. (2007) for motorcycles, and Muñoz et al. (2016) for bicycles. Mobility services subscriptions are less addressed in the literature but are beginning to be studied such as in Shaheen & Cohen (2013), with a more qualitative approach. The mobility tools portfolio approach has been introduced by Scott & Axhausen (2006) establishing one of the first model explicitly addressing the mobility tools issue. Since then, Le Vine (2011) brought a more detailed analysis of the mobility tools holding concept, and several recent contributions in Le Vine et al. (2013); Habib & Sasic (2014); Astegiano et al. (2017); Becker et al. (2017) have enriched the field. But those approaches are still limited in the number of considered mobility tools, not often reaching more than four distinct mobility tools at the same time, and none has yet been conducted on the Paris region.

The intermodality field is a lot less researched, and not always available in English. Most of the existing papers deal with freight intermodality such as Jones et al. (2000); Crainic & Kim (2007). They highlight the difficulty to define intermodality, which shows the importance of describing what is considered as intermodality before studying it. There often is a confusion between intermodality and the mutlimodality phenomenon studied in Massot (1999), which addresses the use of several modes for making a trip at different period of times such as using a car to go to work on day 1 and using a bike sharing system for making the same trip on day 2. Intermodality happens for trip where a mode combination happens, such as using a bike to reach a bus stop. Most of the papers studying intermodality have a statistical description approach, see Lichere & Foulon (1999); Gebhardt et al. (2016); Richer et al. (2016); Oostendorp & Gebhardt (2018) for instance. The intermodality modelling approaches are rather focusing on the route choice in Florian (1977); Boile et al. (1995); Ziliaskopoulos & Wardell (2000); Leurent (2006), instead of addressing intermodality demand modelling.

Considering the recent stages of development of the mobility tools holding and intermodality research fields, this dissertation adopts an exploratory perspective, trying to give a detailed picture of the study phenomena before building modelling specifications.

Methods

Diversified approaches and methods are needed to assess the mobility tools holding and intermodality mobility phenomena involving urbanism, geography, sociology, demographics, psychology, civil engineering, economics or environmental studies. While this research can not claim to belong to all of these, some qualitative interpreting belonging to these can be found in this manuscript, with a stronger link with the socio-economic and civil engineering research fields.

The first and more conventional method is the literature review. This systematic and mandatory method employed by any research and in every dissertation enables drawing a general picture of the state of the knowledge concerning the research topic. It grants the opportunity to set the framework of the research, but also to define and set the main concepts, especially for topics not fully defined in the existing literature.

The second most represented method relates to the systemic socio-economic analysis of urban mobility, aiming to build a holistic description of the study phenomenon. This systemic analysis is lead with a focus on describing supply and demand indicators and to observe how these result in an equilibrium. More precisely, it discusses how the demand is impacted by the socio-economic setting an by the supply. This approach is not directly associated with technical analysis tools, but is a general way of structuring concepts along this manuscript.

After these first general methods for addressing a problem, more specific technical methods are developed: The first and main technical method relates to discrete choice modelling, a well-established field of econometrics. It encompasses mathematical tools to model individual behaviours and choices. This method is a direct application of the economic utility theory, considering that each choice alternative is associated with a conceptual scalar function of the quantitative attributes of an alternative, named utility value. The choice alternative associated with the highest utility value is the alternative selected by the study individual. This first deterministic method becomes probabilistic when an error term is added to the utility function. In this probabilistic setting, the weight of the choice alternative utility as opposed to the other alternatives determines the probability of choosing this alternative. The mathematical formula to computes the weight comes from assumptions on the error term. In this dissertation, discrete choice models are developed for mobility tools holding choices and for intermodality mode choices, and the candidate mathematical formulation belongs to the logit family. This logit family linked with the logistic distribution is one of the most common error term distribution in the transport research.

Spatial analysis tools is the second technical method type employed in this research as mobility is the result of the distribution of a population and activities on a field. A Geographical Information System (GIS) software is used to analyse the geographic distribution of study individuals and their characteristics, and of trips. Combined with a transport modelling package, they are used to reproduce associated trip travel times, and to estimate intermodal trip travel times from origin and destination of trips data.

A third technical method type is about descriptive statistics to highlight the main patterns of the study phenomena. Aside traditional average and relative deviation computations, several graphical displays are proposed such as a decision tree scheme and diagrams. These are completed with correlation analysis distances displaying the objects often appearing together or that are often dissociated. These methods are applied on a dataset issued from an extensive Paris region household travel survey but not built for the sole purpose of this research.

In order to describe the structure of metropolitan mobility models, a mixed model theory comparison approach is employed. It involves synthesizing model technical documentation, identifying relevant comparable indicators and defining a typology enabling an easy access to model features and highlighting model differences.

Thesis structure

This dissertation is organised in six chapters: the first two chapters describe the frame of this research, while the following three chapters focus on the mobility tools holding phenomenon, before a last chapter dedicated to intermodality analysis.

Chapter 1 describes the systemic metropolitan mobility description approach. Its aim is twofold: to describe the mobility system objects and to assess the potential data sources feeding such analyses. It sets up the thematic supply, demand and uses frame of the mobility analysis linked with the field characteristics, and general concepts employed in this research. It also discusses the ability to observe mobility phenomena with the use of observations from different data sources with different ranges and reliability levels.

Chapter 2 focuses on travel demand planning methods. This chapter investigates the modelling techniques employed to represent metropolitan mobility and the need for expanding the mobility planning tools. It first describes the general four step model structure from which most of the recent models originate. Second, it defines a model analysis framework highlighting model characteristics and specificity. Third and last, it provides a comparison of the Paris region models illustrating the need for a more complete mobility representation.

Chapter 3 addresses the mobility tools holding phenomenon. It aims to conceptualize and define the mobility tools holding phenomenon, its diversity and the notion of portfolio of mobility tools, and the literature review of the modelling techniques dedicated to it. This literature review starts with aggregated models focusing on separate mobility tools before presenting more complex disaggregated models and portfolio approaches combining several mobility tools in the same choice process. These constitute a starting point for specific statistical analyses.

Chapter 4 investigates the mobility tools holding phenomenon as a household or individual choice. It statistically evaluates the diversity of mobility tools in the Paris region, including the driving license, the car, the car parking space, the bike, the PT pass and the bike sharing holding. Geographic, demographic and socio-economic descriptors of each tool separately are displayed, before focusing on the combination of multiple mobility tools into portfolios patterns. It involves several statistical methods including dedicated statistical representations developed for this study at the individual level. This analysis is based on the processing of the EGT 2010 Paris region household travel survey, with a specific focus on a study subpopulation to simplify the household versus individual choice dilemma: the individuals in one individual households. This study subpopulation is also studied in the following chapters.

Chapter 5 puts forward mobility tools holding models focusing on joint holding effects an provides estimation results for the studied populations. After building separate models for each mobility tool, a joint model of portfolio choice is built. The approach is refined by highlighting the most common portfolios and by distinguishing population segments associated with different mobility needs: the active study subpopulation. It leads to accounting for the effect of constrained home-work trip characteristics on the mobility tools holding choice. This last element requires the computation of unobserved trips travel time with an existing transport model for the home-work trip, linking mobility uses behaviour with the mobility tools holding decision.

Chapter 6 brings together mobility tools holding and intermodal trip making in order to study their interactions in commuting trips. Intuitively, intermodality requires specific mobility tools portfolios. First, the intermodality phenomenon is researched and defined. Second, a statistical study of the descriptors of intermodal trips and trip makers displaying the socio-economic and geographic patterns of intermodal individuals and intermodal trips is conducted. Third, a modelling approach built on specific segment conditions favouring intermodality study is proposed. It enables to determine the specific demand segment on which intermodality is a relevant alternative.

This manuscript is concluded with final perspectives on how to improve the study and modelling of mobility tools holding and intermodality. The conclusion includes recommendations on the potential inclusion of these phenomenon within applied mobility demand models.

Research communication

During this doctoral research, a set of communications has been produced:

- *A comparison of Paris models "Comparaison des modèles franciliens"*, 2017 by Trouvé, M. and Leurent, F.. This communication has been podium presented at the November workshop of Paris modellers "Comité des modélisateurs franciliens" lead by DRIEA IF in Paris, France and inspired the second, third and fourth sections of Chapter 2.

- Trouve & Leurent (2018): *Modeling Urban Mobility at a Metropolitan Scale: a Comparison of Paris Transportation Models*, 2018 by Trouvé, M. and Leurent, F.. This communication has been podium presented at the Transport Research Arena (TRA) 2018 in Vienna, Austria. It has been published in the conference proceedings and inspired the second, third and fourth sections of Chapter 2.

- Trouve et al. (2018): *Private Motorization in Worldwide Developing Countries Metropolitan Areas: Patterns in the early 21th century*, 2018 by Trouvé, M., Lesteven G. and Leurent, F.. This communication has been podium presented at the PIARC International Seminar 2018 in Arusha, Tanzania.

- Trouve et al. (2020): *Worldwide Investigation of Private Motorization Dynamics at the Metropolitan Scale*, 2020 by Trouvé, M., Lesteven G. and Leurent, F. This communication has been podium presented at the World Conference on Transport Research (WCTR) 2019 in Mumbai, India. It is being published in the conference proceedings.

- *Motorcycle motorization in the world "Motorisation motocycliste dans le monde"*, 2019 by Trouvé, M., Nemett, L. and Lesteven, G.. This communication has been made for the November 2019 COSMOS symposium "COnnaissances Scientifiques pour les MOtocycleS" organized by IFSTTAR and CEREMA in Paris, France.

Chapter 1

Description of Mobility in a Metropolitan Area

Introduction

Metropolitan mobility involves the study of the transport of peoples on a metropolitan field. While transport refers to the movement of an element from an origin point to a destination point, metropolitan mobility specifies this approach. It narrows the topic to the study of people's transport within a metropolitan environment, to focus on individual decision-making not including logistic transport involving company decision-making. Yet it also broadens the topic by adding socio-economic effects impacting the metropolitan mobility demand. This narrowing also enables to mainly access daily mobility associated with daily needs on a small geographical scale as opposed to more occasional long trips involving less usual behaviours.

The metropolitan scale is a logical and favoured scale to manage mobility. From a mobility planning authority perspective, managing metropolitan mobility is a way to handle the flows of individuals generating social, economic and cultural activities on a territory. The theoretical and operational mobility planning studies and models are also built at the metropolitan scale enabling cities and model comparisons, and to answer this need for mobility and activity growth forecast.

While the strict focus on metropolitan mobility makes sense, it is also consistent from an urban management perspective. Indeed, mobility is tightly linked with urban development as both are parts of the same metropolitan system. The urban growth is a major challenge for cities around the world – whether in developed or developing countries – so is the associated metropolitan mobility development. At a time period when sustainable development is a major international concern and when the mobility sector is a major greenhouse gases producer, understanding the drivers of metropolitan mobility in order to promote greener mobility solutions is also key. So studying metropolitan mobility is indirectly and directly related to the tackling of major global challenges.

But studying mobility is not straightforward as it is in an open system with many external or occasional disruptions and it can be difficult to observe. It is indeed complicated to state when the mobility system is "normally" functioning and when it is not, especially in wide metropolitan areas with large mobility networks and a lot of daily events where there always is an unusual event happening. It is also very field dependent because each metropolitan area has its own geographical constraints, socio-economic characteristics and cultural background each translating into various mobility behaviours.

In order to better understand mobility tools holding and intermodality within this metropolitan mobility framework, it is important to understand how this metropolitan mobility is organized and analysed, before focusing on the metropolitan mobility modelling in the next chapter. To set up the field basis, a first section deals with the general characterization of metropolitan mobility to enable a systemic approach of the metropolitan mobility phenomenon. It is followed by a second section describing the ways metropolitan mobility is measured to understand its related data gathering process and data quality limitations.

1.1 General Characteristics

Mobility is a wide topic and generalization is not always possible. A mobility solution can be relevant in a specific metropolitan area while not at all in another one. The usefulness relies on several geographical, socio-economic and cultural factors. For example, a cable car system makes sense in hilly areas while it does not provide much benefits on a completely flat land. Similarly, implementing a very luxurious and expensive system in a socio-economically disadvantaged area is due to fail. From the mobility management perspective, these issues are solved by matching the supply and the demand for mobility. So understanding mobility involves well identifying and characterizing the mobility supply and demand system on the field study. More practically, transport is often considered as a public service and mobility must also be characterized by its decision-making structure framed by the governance structure. Once this local frame is set, interpreting is possible through generic indicators. This mobility characterization issue is tackled in this section by focusing in turn on the field study features, the governance structure importance through an application to the Paris region, and the identification of key indicators categories.

1.1.1 A field study

With the current demographic and economic growth centred on cities, metropolitan area development is a major challenge faced by urban planners all around the world. This challenge is all the more important than it has strong effects on local economic development and on greenhouse gases emissions, a major concern of the XXIth century. Indeed, it is established that cities with very low population densities and housing neighbourhoods, far from work and leisure places, generate a high transport demand leading to increased traffic congestion and energy consumption, at the root of high greenhouse gases emissions. Studying transport systems with regard to metropolitan and urban characteristics seems a relevant approach enforced by previous studies conducted by Gwilliam (2002) or Tana et al. (2016).

It also involves several research topics, and one of the most important ones is the geographic field because individuals move on a location and this movement is affected by and affects the local topology and overall geography. A major concern within the geographic field of research is the definition of boundaries and the different possible analysis scales. The question of boundaries is a recurring one: while it does not seem hard to set a boundary in the middle of a river – even though it is not so simple to state whether the middle must be defined at a precise water level, at a precise date as it is common knowledge river evolve by growing and moving – or on the top of a mountain, it is difficult to set an urban versus rural boundary. This might seem picky as including more or less a few meters of road in the metropolitan area is not very important. But it has some importance for the mobility study topic: whether a nearby housing area or job center belongs to a metropolitan area influences the overall metropolitan mobility analysis. The issue of scales is not only geography specific, but it is nonetheless important because a study field is often made of different zones displaying geographical inequalities. So it is possible to make general observations that do not stand at all on a specific zone within the study field. For example, studying car holding in London should differentiate the congestion charge zone from the others zones within the overall London metropolitan area study field. This subsection investigates these questions of scales and boundaries which specify the choice of focusing on studying mobility on metropolitan areas.

First the general scale approach. As stated in the introduction, mobility mainly is a metropolitan phenomenon. The urban unit is based on some geographic homogeneity within the study field, as opposed to rural environment displaying other activity and density characteristics. This approach varies from previous more general national scale research. The latter displayed the advantage of having lower boundary issues because it is most of the time legally defined by governments and not by the researcher, and of having national count data availability. But they mix different cases such as isolated villages and intense urban centres, each displaying important mobility pattern differences. Indeed, national transport analysis catches a lot of different transport types: interurban transport, touristic mobility, metropolitan mobility and urban logistics, home-work mobility, and many other activity mobility. This dissertation focuses on regular behaviours observed on the daily metropolitan mobility rather than on occasional touristic mobility and others, so this justifies reducing the scale to the metropolitan area. A smaller scale could have been possible but it would have raised the issue of having too many mobility behaviours involving elements out of the study field.

The question of boundaries is also important because it is not relevant to arbitrarily draw a circle on a map and to state "this is the study field". The study field must be defined depending on the study phenomenon in order to avoid breaking continuous elements of the study phenomenon, and to show some overall continuum consistency. It would not make sense to study hydrology and to have a study field with boundaries ending up in the middle of a water table. Metropolitan mobility is the topic of this dissertation, so metropolitan boundaries are the relevant one here. The French statistical analysis institute INSEE defines an urban unit as a continuous built environment reaching a minimum number of inhabitants. A built environment is continuous if any building is less than 200 meters away from another building, converting the need to have an overall continuous study field. This definition includes exceptions accounting for specific topological cases. While the urban unit definition matches the agglomeration definition, the metropolitan area definition is wider and encompasses any communes with at least 40% of the active population going to work in the urban unit – or agglomeration –. The study field boundaries must also be selected by accounting for data availability. Defining a study field with a very detailed boundary but without any existing data available or displaying data collection issues does not make sense too. Aside the theoretical selection, practical criteria for the field boundary definition must be included. These criteria can involve some administrative authorizations to conduct analysis on a territory, so administrative boundaries are very important to account for too. For the Paris case, the metropolitan area is already well defined, but there is not much data for this exact scale. Geographically, the Paris metropolitan area is very close to the Paris region and it is generally assumed that both are almost equal, while there is a lot more data available ate the administrative region scale. Travel survey data is collected at the region scale for instance. That is why the remaining of this dissertation focuses on the Paris region study field and boundaries. This field selection matching the metropolitan area is also relevant to study mobility because the metropolitan areas involves a lot of inner flows connected with the centre agglomeration.

1.1.2 An administrative governance frame

After setting up the study field, understanding the administrative governance of the mobility system enables highlighting which decision is taken by which organism and whether it is framed in an overall state strategy or to satisfy a strictly private or local demand. Metropolitan mobility development can be considered the result of a competition among the different mobility actors framed by the hierarchy defined by the governance structure. There is a high number of possible metropolitan mobility governance schemes for each mobility network, but they can generally be qualitatively assessed by the importance of the public entities versus private ones, and then by the importance of the local entities versus the wider national ones. These points can be illustrated with the Nairobi case described in the Digital Matatus project[1]: in the Nairobi metropolitan area, the public transit system is almost non-existent and some private buses also known as "matatus" replace it. But most of these are not coordinated on a larger scale than a line, so the

[1] http://www.digitalmatatus.com

governance is more private and on a local basis for the public transport network. A more detailed picture of metropolitan governance description is displayed with the case of the Paris metropolitan mobility governance and its most recent history explaining current stakeholder positions.

First concerning the road network, the French state is the owner of the main highways and national roads. Some highways can be leased to private companies, but most of the ones in the Paris region are state owned and run. The departmental road with a speed limit between 80 and 90km/h are managed by the department and the other communal roads are managed by the communes. So each department and each commune is responsible for its own road network. Concerning the Paris city, all of the roads in the Paris department – including the first Paris ring road which physically rather is a highway – are considered as communal roads managed by the city of Paris. So the road network is owned and managed by a mix of State and local public entities, and parts of it can be leased to the private sector for renewable fixed terms.

The public transit network has a more complicated history, with a division between the metro and bus network of the Paris city, and the regional trains and bus network. The Paris city public transit network used to be entirely managed and developed by the RATP, a French public company in charge of the network operations and owning the infrastructure, administrated by the French State. Within a decentralization legislative process achieved in 2015 with the "Nouvelle Organisation Territoriale de la République"(NOTRe) law, the mobility organization competence has been transferred from the State to the regions. The Paris region became more important and mostly manage mobility through Ile-de-France Mobilités[2], the Paris region mobility managing entity. The RATP still exists, managing transit lines and owning the metro infrastructure, but the bus and train vehicles are now owned by Ile-de-France Mobilités. This evolution is in line with the European Union directive to open the rail networks to competition among operators.

For the remaining of the Paris region public transit network, the regional trains are managed by the SNCF, the historical public French company managing and owning the national rail network. Technically, SNCF Mobilités is responsible for the train operations and SNCF Réseaux manages the infrastructure, but both belong to the same SNCF holding company administrated by the French State. For the suburban bus network, it is a conglomerate gathering SNCF, RATP and other bus operating companies, named OPTILE that is managing the operations. Like

[2]formerly named Syndicat des Transports d'Ile-de-France (STIF)

the Paris city, this suburban network mobility is now managed by Ile-de-France Mobilités.

While there are a lot of public companies within the public transit network of the Paris region, and that used to lead this network development, Ile-de-France Mobilités is now the key decision-making entity for managing the overall public transit network. Even though RATP and SNCF have historical strong links with the Paris region public transport networks, they do not have anymore the decision-making power. All of the companies involved in the Paris region public transit running have an official contract with Ile-de-France Mobilités enabling them to conduct the operations for a fixed-term period. At the end of this period, the contract is proposed again in an open public market competition. This contract also involves sharing data collected on the managed mobility network with Ile-de-France Mobilités.

Concerning the pedestrian walkways, cycle lanes and the more general urban development, each commune is responsible for its development and some projects can be financed by larger administrative entities such as the department, the region or the State. So the local commune is the key decision maker but can be supported and influenced by larger administrative entities.

Because a mobility infrastructure development often involves almost all of these networks, all of the entities mentioned are often involved in most of the mobility projects, but with varying decision powers. But it can be considered that the administrative governance is relatively decentralized with the different administrative scales represented in the decision-making process. The private sector is not much represented in the mobility management, even though heavily involved in the infrastructure construction.

This administrative governance has recently been challenged with the introduction of new mobility services, such as the free-floating bike sharing and electric scooter sharing services in 2018 and 2019. As a local entity, the city of Paris has enacted a municipal by-law framing its use in the Paris region, while the Paris region had no legislative or executive power on these new services. The French State is still working on a law to frame this mobility service use on a national scale.

1.1.3 Key indicators

Because mobility development is linked with the socio-economic development, a mobility analysis must encompass information on each of these topics and observe the correlation and causality links among each associated set of indicators. These indicators can be considered like descriptors or proxy of the complex mobility supply, demand and uses system and can be sorted following these. So indicators of the socio-economic characteristics of an urban area rather are related with the mobility demand, while indicators on mobility networks development are rather related with mobility supply. Both of these are confronted within the mobility uses characteristics describing the actual mobility making such as flow or traffic indicators.

The mobility supply indicators include any indicator referring to the infrastructure or quantifying the level of services of the different mobility modes. Indeed, the supply can be assessed by the average length of mobility networks, the number of vehicles, the price, the operating schedule, the frequency, the average operating speed, the speed limits. The availability of intermodal platforms enabling switching from a mode to another one is also relevant and the connection to interurban networks too. A mobility supply analysis should also account for the different mobility modes and services available in the metropolitan area.

Indicators of mobility demand are less directly related with the mobility field. They include any information on social, economic, urban or even cultural characteristics of the metropolitan area. The most traditional indicator used in mobility modelling is the income and its distribution within the population, but many others can be accounted for such as the gender ratio, the age pyramid, the different economic sectors, the active population ratio, the household composition, the mobility equipments diffusion, the activity organization in the metropolitan area, whether it is very centralized or gathered around several employment basins. Other indicators of air quality could also be incorporated to account for environmental issues.

Last, the description of the current mobility supply and demand equilibrium with details on the mode shares in daily trips, the trip number and their average duration and distance, their spread among the metropolitan area. Collecting these indicators enables to draw a general diagnostic to identify the main features, strengths and weaknesses of the mobility system of a metropolitan area. An example of such a diagnostic is displayed in Figure 1.1, Figure 1.2, Figure 1.3 and Figure 1.4 for the Paris metropolitan area.

Focus on Motorization indicators

Private motorization is a standard indicator of mobility tools holding widely produced. It can be defined as the motorized vehicles degree of penetration within a private transport system, and translates into several indicators:

The most common indicator is the vehicle density, expressed as the average number of private vehicles per 1,000 capita or household. It enables measuring the capacity of the motorized modes on a territory. From a metropolitan mobility perspective, this indicator illustrates the diffusion and the rank of the related private motorized modes in the transport modes mix. One main issue is that it often does not account for unregistered vehicles or for vehicles registered in neighboring geographical areas.

The motorization ownership rate expressed as the share of households owning a motorized vehicle. It relies on the definition of households that is sometimes not clear such as observed by Randall & Coast (2015). It does not show the overall motorized vehicle modes capacity. Instead it is an evaluation of the penetration of the motorized vehicle good in the household market. The motorization rate is based on households, relying on the implicit assumption that motorized vehicles are expensive and durable goods held at the household level, which stands less for motorcycles.

The percentage of motorized vehicle trips is not often used under the meaning of motorization but it is definitely a measure of motorized vehicle use importance through its modal share. It can be considered as a diffusion indicator. Its main drawback is that is does not evaluate well the physical impact of motorized vehicles on the transport system as it accounts for the frequency of motorized vehicle use and not really its intensity. It is also heavily linked to its measurement period.

The average number of vehicle-kilometres or vehicle-miles is a last indicator of motorization. It is the number of kilometres of motorized vehicle use, resulting from the multiplication of the average number of kilometres per motorized vehicle by the number of motorized vehicles. It completes the last indicator by incorporating the notion of the intensity of the vehicle use.

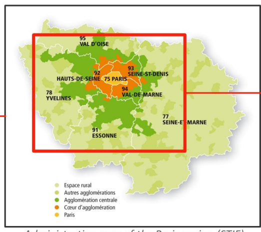
Mallory Trouve

The Paris Metropolitan Area

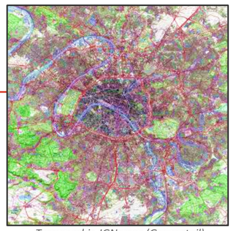
General analysis of the area

Geography

Map of Europe (Google Maps)



Administrative map of the Paris region (STIF)



Topographic IGN map (Geoportail)

It is also known as the Paris Basin, as the ground is lower than average in the region. The Seine river and the Marne river are the main watercourses.

The Paris Metropolitan Area is the located in France. It is made of the administrative and economic capital and its suburbs. France is a very centralized country and this main central area contributes for **30%** of the national GDP.

The metropolitan area includes :
+ the **Paris** administrative department (75);
+ the "**Petite Couronne**" Hauts-de-Seine (92), Seine-Saint-Denis (93), Val-de-Marne (94);
+ parts of the "**Grande Couronne**" Yvelines (78), Essonne (91), Val-d'Oise (95).

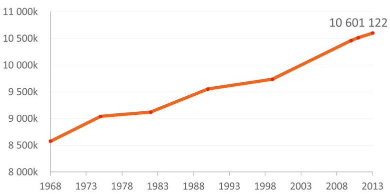
The soil is very calcareous and former excavations can be found. This topology enhances smog effect during pollution peaks.

Overall surface:	2 844.8 km²
Maximum elevation:	11 - 216 m
Climate:	oceanic, mild
Time Zone:	UTC+01:00

Paris Metropolitan Area 2013 (Source : INSEE)

Population

Paris Metropolitan Area's population



(Source : INSEE)

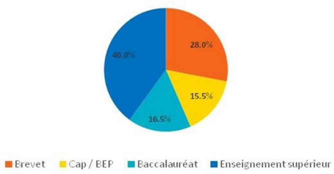
The area is developped and is now expanding slowly. Its population is growing at a rate of **0.5%** per year, and is skilled. Paris is very dense while the suburban areas are more residential.

Density:	3 726.5 hab/km²
Households #:	4 516 754

Paris Metropolitan Area 2013 (Source : INSEE)

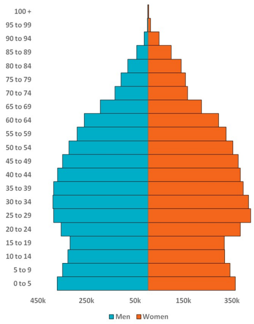
The age pyramid is not straight, illustrating a main student and working population from 20 to 65.

Level of education



Paris Metropolitan Area 2013 (Source : INSEE)

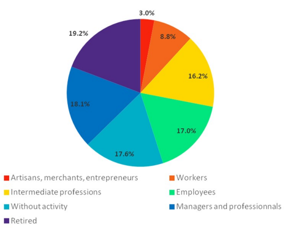
Age Pyramid 2013



Paris Metropolitan Area (Source : INSEE)

Economy

Socio-Professional categories 2013

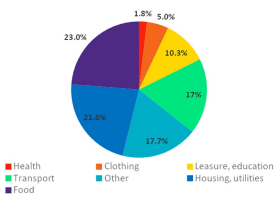


Paris Metropolitan Area (Source : INSEE)

GDP (region):	642 523 M€
GDP/hab (region):	52 788 €
HDI (country):	0.887
Gini Index (region, after tax):	0.343
Median Annual Income:	22 186.50 €
Poverty ratio:	16.3%
Labour Force:	76%
Unemployment ratio:	12.6%

Paris Metropolitan Area 2013 (Sources : INSEE, OECD, UNDP)

Household expenses 2013



Paris Metropolitan Area (Source : INSEE)

The socio-professional categories match the education level of the Paris Metropolitan area: there is a very high ratio of skilled jobs.

The household expenses spread illustrates the importance of transportation which is one of the main costs. This is typical of developped cities that are now growing steadily.

Figure 1.1 – Paris mobility description (1/4)

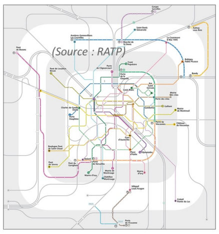
Transportation Supply

Main Urban Networks

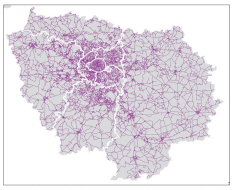
The main planning agency of the Paris Metropolitan Area is the STIF, organizing the contracts with the operators RATP, SNCF and OPTILE.

1 ticket:	1.90 €
1 ticket to airport:	8.00-9.30€
weekly pass:	19.25-22.15€
annual pass:	696.30-803.00€

(Source : RATP)



Map of the public transportation rail network (STIF)



Map of the public transportation network (STIF)

Current policies are promoting the use of public transportation over cars, reducing the road sizes and the number of parking lots in the city center.

The Public Transport is developped, with light rail, heavy rail, buses, bus lanes, a few BRTs.

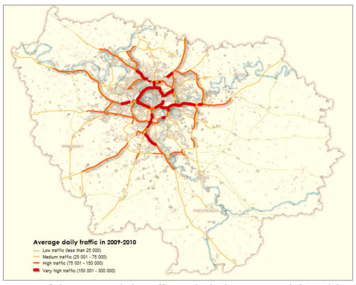
	number	length	vehicles
bus lines:	1505	33 047 km	2839
metro lines:	16	218 km	693
light rail lines:	7	83 km	213
RER lines:	5	600 km	449
reginoal train lines:	8	850 km	740
TOTAL:		34798 km	4934

Paris region 2013 (Source : STIF, OMNIL)

The metro network has an amorphous shape enclosed by a light rail circle. The RER network linking the suburbs to the city center is radial, while the bus network has mainly been designed to cross the Seine River and to link isolated areas to the metro network. It is operated from 5:30am to 1:15am (2:15am during the week-end days).

Average age of the rolling stock (heavy rail - RATP):	32 years
Average age of the rolling stock (light rail):	10 years
Average distance from a metro station in Paris:	less than 500m
# Trips per day in 2010:	41M
# Public Transit trips per day in 2010:	8.3M

Paris region 2013 (Source : STIF, OMNIL, RATP)



Map of the average daily traffic on the highway network (IAU idF)

The road networks has a high influence on the area: A first very crowded beltway called the "Boulevard Périphérique" encloses "Paris Intramuros" and is a physical frontier that has a very high socio-economical impact. There is a second ring-road 10kms away called the A86, and a third one the "Francilienne" which is not closed yet. A fourth unfinished ring-road - the "Grand Contournement de Paris" - allows avoiding getting in the Paris Area.

# Car trips per day in 2010:	16.1M
Speed Limit on the Périphérique in 2010 (2014):	80km/h (70km/h)
Average speed on the Périphérique in 2010:	37km/h
Speed Limit in cities:	50km/h
Speed Limit on highways:	110km/h

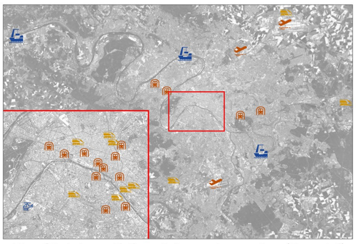
Paris region (Source : STIF, Ville de Paris, V-Traffic)

The daily traffic map shows the radial highways and the Boulevard Périphérique the most congested roadways with daily traffic jams.

Connections

The Paris Metropolitan Area has **3** main harbors (Genevilliers, Bonneuil-sur-Marne, Limay) under the authority of Ports de Paris. It is the **2nd largest** inland port in Europe, with its **6** multimodal platforms and **6** active container terminals.

There are **1125** public transit rail stations in the Ile-de-France, **20** of those dealing with more than **10M** passengers per year.



Map of Paris Area with the main transport connections (Geoportail)

The airport authority manages **3** airports, **1** heliport and **10** general aviation airfields. The main airport is **Paris-Charles de Gaulle (CDG)**, the largest hub in Europe deserving **319** cities, and a hub to fly to African countries.

In the Paris Area, there are **5** main train stations with **more than 100,000** traveler per day: Gare Saint-Lazare, Gare du Nord, Gare Montaparnasse, Gare de Lyon and Gare de l'Est. All of them are connected to a metro station

Mobility services

(Source : www.patrickjouin.com)

Paris is a pioneer in shared bikes programs with its Velib' service, gathering **23,600** bikes in 2015 dispatched over **1,751** stations with more than **100,000** uses per day.

(Source :AUTOLIB)

Autolib' is an electric carsharing network started in 2009. It had **3,931** bluecars dispatched over **1,096** stations with **6,217** charging terminals in Paris, for **15,000** uses per day in 2016.

57 Véligo secured bike-parks have been implemented at train stations, improving intermodal commuting with biking and using the public transport.

Station Véligo (STIF)

There are **22,000** taxis in the Paris region, and 3 main taxi companies: Taxis G7, Les taxis bleus and Alpha Taxis.

Taxis are now in competition with **15,000** transportation network companies - which cannot be hailed - such as UBER, LeCab , Chauffeur Privé, Marcel or Allocab .

A small river shuttle service along the Seine River called Batobus exists. It goes over **9** touristic areas and is not much used for daily commuting.

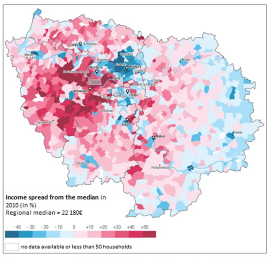
The transport authorities in the Paris Metropolitan Area aim to improve the mode shift from individual cars to public transit or biking and walking. As a result, the streets are being renovated to grant less space to cars and to be bike friendly and more walk friendly. Indeed, walking had a **39%** mode share in 2011 and there were **2,042** km of bike lanes in 2015.

(Source : www.projets-architecte-urbanisme.fr)

Figure 1.2 – Paris mobility description (2/4)

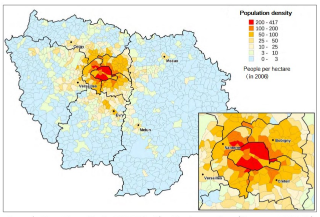
Travel Demand

The Demand induced by Population Factors



Income spread in 2012 in the Paris region (© IAU idF)

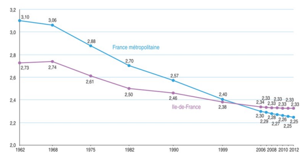
The Income spread map shows a historical division between the East and the richer West, especially in the former areas where noble families lived.



Population Density in 2006 in the Paris region (Source: DRIEA)

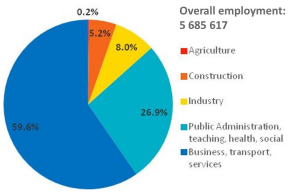
The population density map shows the population is **very centralized in the downtown areas with a few suburbian hubs**, which is very common for European cities. This urban centralization generates a high demand for traveling between the center and the suburbs, explaining the radial development of the transportation networks.

The number of capita per household evolution shows the average trend of a leveling population. An important step has been reached around 2000 when the capita per household in the Paris region has overcome the national one for the first time. In 2012, there were **2.33** capita per household in the Paris region.

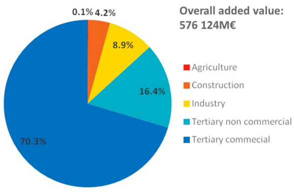


Capita per Household Evolution in the Paris region (Source: INSEE)

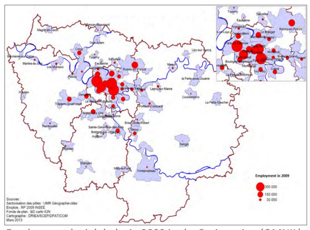
Employment vs Added value per sector



Employment per sector of activity in 2013 in the Paris region (Source: INSEE)



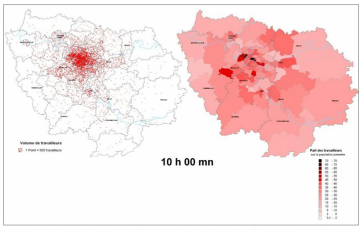
Added value per sector of activity in 2013 in the Paris region (Source: INSEE)



Employment by job hubs in 2009 in the Paris region (OMNIL)

The sectors of activity are typical for a developped city : the tertiary sector is the most important one, which a quasi non existant primary sector. As Paris is the political capital of France, the administrative and public sector is important too.

The employment is also very centralized, but some other growing activity centers are appearing in the suburbs. It is also important to notice that the financial district is located by the city center at La Défense, contrary to American cities.

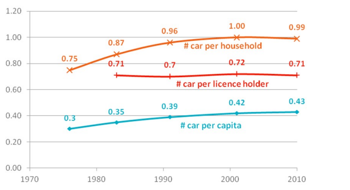


Workforce Spread in 2010 in the Paris region (Source: DRIEA)

Mobility Factors

# cars:	5.0M
Licence holders ratio:	0.60
# daily trips per car:	3.7
Average daily km per car:	26.3
Average daily use per car:	93min
# capita per car-trip:	1.48
Average time per car-trip:	23min

Paris region 2010 (Source: DRIEA)



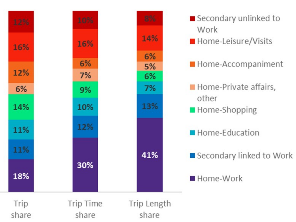
Evolution of the Car ownership ratio in the Paris region (Source: DRIEA)

	# car per household	# car per licence	# car per capita
Paris	0.49	0.41	0.26
Petite Couronne	0.92	0.70	0.39
Grande Couronne	1.35	0.86	0.53

Paris region 2010 (Source: DRIEA)

The car holding ratio are reaching a peak since the 2000s at **about 1 car per household**. Yet this ratio must be analyzed carefully as it heavily relies on the location of the household: It goes from 0.49 in Paris to 1.35 in the Grande Couronne. The number of car per license holder is also steady since the 1980s, so this peak probably comes from a peak in driving license ownership.

On average, a car trip lasts **23 minutes**, while a car is used **93 minutes per day**, on **26.3km** with an **occupancy ratio of 1.48**. This ratio is low and means that there are more cars with less than 2 person on the roads. But this might not show the actual situation, where a global car sharing trend is hitting the world, and European cities especially.

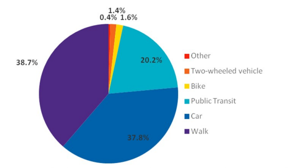


Paris region 2010 (Source: STIF)

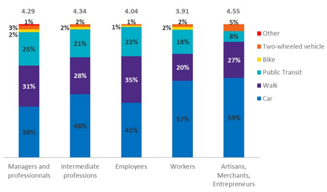
The mode share is typical of a very developped city with an efficient public transport systems: walking is the primary transport mode with **38.7%**, followed by car and public transit. Even though the main motivation for travelling is commuting to work, its share in the trip time and in the trip length is more important than in the overall trip share. At the opposit of American cities, the more skilled a worker is, the less he'll use a car and the more he'll use public transit.

# trips per day:	41.1M
# trips linked to Paris:	12.2M (29.7%)
# trips linked to Petite Couronne:	16.7M (40.6%)
# trips linked to Grande Couronne:	18M (43.8%)
Average trip length:	4.4km
Average daily trips per capita:	3.87
# PT pass holders:	4.0M (33.5%)
# Velib' annual subscribers:	300k (2.5%)
# Autolib' annual subscribers:	109k (0.9%)

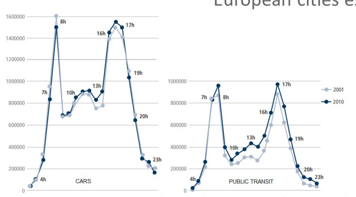
Paris region (Source: STIF)



Average mode share in 2010 in the Paris region (Source: STIF)

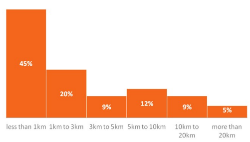


Average mode share per socio-professional category in 2010 in the Paris region (Source: STIF)

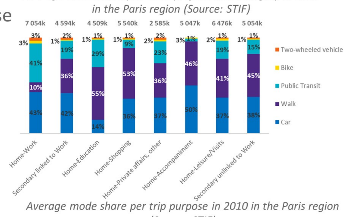


Average Person-Trip Starts per hour in the Paris region (Source: STIF)

The graph on the left illustrates the travel behavior, with very high peak periods in the morning and in the evening, and a small third one at lunch.



Trips share per trip length in 2010 in the Paris region (Source: STIF)



Average mode share per trip purpose in 2010 in the Paris region (Source: STIF)

Figure 1.3 – Paris mobility description (3/4)

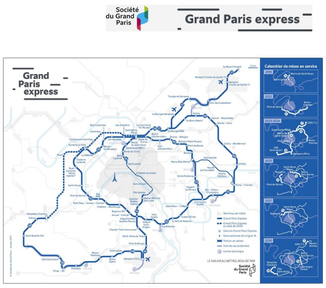
Analysis & Diagnostic

Current development

Urban projects in Paris (www.societedugrandparis.fr)

The Paris Area is facing the challenges of developed urban areas. It balances its transportation expenditures among 3 objectives: maintaining its ageing infrastructure, developing the existing network and promoting new transport modes.
The rising concerns about greenhouse gases, fine particle emissions and green development also have a high impact on the urban transport network evolution.
Finally, the effect of globalization and the endless need to travel faster is putting a pressure on the planning agencies to continually improve the service, offering more connexions, more efficiently.

The highway network is not growing anymore, but existing axis are being maintained and modified. In Paris, these modifications are mainly lane reductions and quality improvements of urban spaces.
Until today, diesel vehicle have been very subsidized by the French government (62,4% of cars in France in 2014). Yet, the increase of pollution peaks in 2016 – mainly caused by heating and driving – has motivated the authorities to toughen policies toward diesel vehicles. The Paris mayor even plans to ban them from downtown in 2020.



New metro generation (www.societedugrandparis.fr)

Improvement of urban space project in the Paris region (www.hauts-de-seine.fr)

After a decade with limited investments in the public transit (no development of the underground network, building of light rail circle lanes around Paris), an ambitious **Grand Paris Express project** is undergoing to enhance the connections between Paris and the Petite Couronne. The aim is to build 4 new metro lines, 4 extensions of existing metro lines and 72 new stations for about 24.9M€.
The Paris application to the Olympic Game 2024 may add some more pressure on this project, as it would be required to ensure the good transportation of supporters across the area.
The head of the planning agency recently expressed the wish to develop cableways, and water taxis along the Seine River.

Analysis of the Transportation System

Strengths

- High and growing investment expenditure in the Public Transit system (more than 3.5B€ yearly)
- A very diversified transport supply with many modes available, especially shared ones.
- An effective Public Transportation system in Paris city used by different socio-professional categories
- Public authorities aware of sustainable development challenges

Weaknesses

- A high air and noise pollution level with many pollution peaks in 2016
- An automobile park not diversified with many diesel vehicles running and only a few electric vehicles
- Public governance conflicts among the city of Paris, the region and the French state
- A poor connection of the Public Transportation system between Paris and the suburb, and among different suburbs

Evolution opportunities

The main effort should be concentrated on the 2 main weaknesses of the Paris area transportation network: the **automobile pollution** and the **lack of connection with the suburbs**.

As France is a leader in electric energy production with its nuclear energy, a large **promotion of hybrid and electric vehicles** could help solve the air pollution issues coming from diesel vehicles. **Encouraging shared driving and developping the public transport network** could also help reduce those problems.

The other opportunity is to create more links with the suburb. Improving RER (connecting the suburb to Paris) quality of service while enhancing the accessibility of RER stations with buses, shared vehicle stations, car parks and bike parks.

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SGP – www.societedugrandparis.fr
STIF – www.stif.info
UNDP – www.undp.org
VELIB – www.velib.paris

Icône : Gleb Khorunzhiy, RU ; Nick Holroyd, US

Figure 1.4 – Paris mobility description (4/4)

1.2 Mobility Measurement

While the understanding of mobility must be systemic because of its many side and combined socio-economic effects, it generally is based on more detailed information collected at the household or individual level. The need for both social and physical information is high to illustrate and feed the metropolitan mobility analysis. This need comes from two aspects of mobility which is at the same time made of physical movements and of a social demand for interactions and connections. It is all the more complex since practicing mobility is in line with space and time. Mobility scheduling does not always imply its execution: it is made of planned and spontaneous, regular and occasional decisions. Each trip is the result of psychological and economical behaviours of individual actors. Describing and understanding these behaviours is essential for analysing trip-related decisions such as route and mode choice, as well as mobility tools holding such as motorization and subscription to mobility services.

This section aims on emphasizing and making an organized presentation of mobility measure concepts and of the different instruments used to deeply understand mobility and its stakes especially regarding to route, mode and mobility tool choices. In order to fulfil this objective, mobility element concepts are presented to give an overview of what observations of mobility can be captured. Then a specific focus is made on the reference travel demand data tool linking socio-economic characteristics and travel behaviour, the household travel survey. Last, general sensors and survey techniques including emerging mobility measurement opportunities and their potential for accessing new mobility data are briefly discussed.

1.2.1 Mobility elements concepts

As exposed, mobility is a complex sociotechnical phenomenon. It requires developing a precise understanding of the different physical, social and economic main concepts involved to establish an accurate mobility measure. The necessary concepts to acquire depend on the entity analysing mobility. The concepts involved in mobility are dispatched among three main typologies: movement execution, traffic flow and behaviours. The movement execution type is based on elemental analyses of individuals or specific places. It faces statistical issues about studying a unique individual case or a set of cases enabling generalization. The traffic flow type is based on general analyses in specific places. It involves flow analyses characterized by flow intensity and flow conditions such as speed and homogeneity ranges. Finally, the behaviour type is based on populations analyses on the field. This last type refers to social studies on local inhabitants' mobility practices and their relation to mobility systems entailing economic phenomenon.

The movement execution can have different elementary units of mobility. Depending on the studies, it can either be the trip or the spatio-temporal location points of a person's or a vehicle's trajectory. This dissertation deals with metropolitan mobility modelling and the usual and more practical unit of analysis is the trip or the trip leg. The unit of movement execution is then characterized with attributes revealing mobility practices. Common attributes include trip route and mode enabling the exploration of transit places and the passenger exposition to encountered environments, the speed which can be used to segment passenger classes, or the trip frequency giving information on the user habits. The trip length, duration and price are also important as they help determine the overall trip cost. The trip must also be embedded in its spatio-temporal framework with information on departure and arrival time and places as all of these pieces are important to understand the trip generation. Eventually an individual's mobility is tightly related to the trip activity motives which are the trip initiating triggers. Among the different trip activities, home-work trips are often considered as the main ones, framing the transport systems as they aggregate into large flows during peak periods. These trip attributes can be further detailed with user's overall trip consumption and travel disposition approximated by the available mobility equipment's' portfolio. Movement executions especially concerns transport stations managing authorities.

These elementary movement executions can be aggregated into traffic flows enabling population mobility analyses. This expansion step allows studying mobility as a population of persons or vehicles, as a fluid mechanics phenomenon. It leads to statistical analysis on a delimited space and period which is used to measure mobility intensity and mode diffusion across an area. This statistical approach relies on group attributes characterizing the flow such as mean, median, variances and standard deviation of the attributes used to describe the elemental movement execution. This approach is relevant at different scales from international to local studies determining traffic conditions and hard spots and is often used by transport operation managing authorities.

The behavioural concepts reveal mobility uses through user's inner motivations and choices. Its principle is to identify and understand mobility preferences and incentives of social groups which influence their mobility practice. It uses a sensitive approach influenced by socio-economic and psychological phenomenon analysing preferences differentiating perceived and real levels of services. Studies on the impacts of prices for the transport users are included in this approach. These are also heavily related to activity motives as a clear distinction can be made between required mobility and recreational mobility. These concepts evaluating socio-economic attributes are often lead by entities trying to achieve equity, social welfare and delivering a public service at a global scale such as transport planning agencies.

Another important aspect of mobility is the issue of scales. Indeed, mobility is realized on different scales and it is impossible to study all of them at the same time. Currently, even the transport models are specific to the studied scale from individual micro-economic scales to flow macro-economic scales. Some try to match these different approaches with intermediate mezzo-economic scales, but in the end each has its own limited range of application.

This scale issue applies to spatial scales ranging from proximity mobility of about 1 kilometre trips, to metropolitan mobility of about 50 kilometre trips, and to interurban mobility of more than 100 kilometres trips. It highly complicates the data gathering process as the chosen spatial scale rarely perfectly fits the administrative breakdowns with available data. Getting relevant data often goes through manually aggregating or disaggregating existing data from official datasets. An example from studying metropolitan mobility is that data is usually available at a regional scale which encompasses but does not exactly match metropolitan borders. Spatial scale issues are all the more complex than studying transport at a specific scale is always impacted by transport at other scales as practical transport is a continuum without limits of scale. Referring to the previous example, metropolitan mobility is affected by interurban transport flows and by proximity flows too. In order to sort this issue, models often consider the flows coming from other transport scales as exogenous variables which deserve a specific study.

Mobility is also subject to time scale issues. Indeed, the mobility behaviour patterns and practices show that mobility can be studied in real-time, on an hourly base opposing peak hours to off-peak hours, on a daily base opposing weekdays to week-end days and to holidays, and finally on a yearly base for annual reports. These different time scales allow respectively analysing precise traffic conditions, the transport system stress within a day, the effect of different events on daily transport and the average efficiency of the transport system averaged over a year. The issue being that observed individuals might be considered very mobile at a given scale while not that much at other scales, thus having an impact on mobility user classes definitions. In order to manage this phenomenon, mobility observation can be repeated or continuous instead of punctual.

Coupling concept types and scale issues shows that getting relevant and complete data on mobility is difficult as it is rare to find data sets encompassing the whole studied case. It is necessary to design and be aware of the principal instruments that can be used to measure mobility, and their range of application.

1.2.2 The reference for mobility instruments: Household Travel Surveys

Among all mobility instruments household travel surveys are usually considered the most complete and accurate ones and are the mobility demand data benchmark. Their results are used for mobility models calibration. They consist of transport surveys lead with large samples. These imply complex logistics and high costs so they are usually conducted about once every ten years. The first guidelines for conducting household travel surveys appear in the 1940s according to the Online Travel Survey manual[3] and they now exist in many developed countries around the world and have been generalised at the national scale – National Household Travel Survey (NHTS) for the United States, National Travel Survey (NTS) in Great Britain, Enquêtes Nationale Transports et Déplacements (ENTD) in France, Kontinuierliche Erhebung zum Verkehrsverhalten (KONTIV) in Germany –. Most of the time, they are driven by national or local transport government departments in collaboration with research institutes. The sample unit of analysis usually is the household because they are precisely indexed, but information can also be collected at an individual and trip scale within the household. This breakdown comes from practical constraints but also from social observations as some mobility decisions are made at the household scale as illustrated in Bhat & Pendyala (2005), such as buying a car or organizing the activities and the associated trips within a day. The spatial scale of national surveys is the nation, but they are sometimes the result of the aggregation of different metropolitan surveys. Eurostat (2015) shows that the European Union is leading discussions about aggregating its member's national travel surveys into a wider European travel survey, but these international travel surveys have not been built yet. Many regions are beginning to consider the advantages that these surveys provide in term of mobility measurement and forecasting, and they develop their own metropolitan travel surveys which require a specific processing as useful data is not always available at this scale. The questionnaires on which these survey are based on are generally very organized and complete, and the topics are layered from the household unit

[3]https://trbtsm.wiki.zoho.com/, accessed on 07/20/2020

of analysis to individual choices, often coupled with travel diaries over a period ranging from a day to ten days.

In France the official national travel survey is the ENTD. The specific regional survey of the Paris region is called Enquête Globale Transport (EGT), meaning global travel survey. Five EGTs have been conducted in 1976, 1983, 1991, 2001, 2010, at about a ten-year rate and the next one is conducted in 2018-2022 so its results were not yet available for this research. Another intermediary EGT was developed in 1997. In 2010, the EGT has been realized under STIF and DRIEA's funding for EUR 6M, in cooperation with local mobility organisms including local authorities, operators and research units. It follows the French CERTU's certification detailed in CERTU (2013) and framing the process to conduct surveys. The survey was conducted by trained interviewers filling paper questionnaires with computer assistance for precisely locating trips. The questionnaires were divided among five themes: Household data, Individual data, Trip data, Trip Leg data and Opinion data. A quota sampling strategy was applied over 109 sectors each representing about 100,000 inhabitants. 18,021 households were interviewed representing 42,529 persons over 5 years old, about 0.4% of the Paris Area's population with information on their travel equipment possessions: driving license, car, bike, motorcycle, PT pass and bike sharing subscription holdings. The survey enabled recording 143,508 weekdays and week-end trips which were attributed a mode associated to one of the six categories: Public Transit, Private Cars, Motorized two-wheeler, Bike, Others (including cab), Walk. The information on travel equipment holding and the different modes available are key elements that enable modelling travel equipment strategic choices and intermodality.

In practice National Travel Surveys are used to quantify travel behaviour and evaluate mobility and its socio-demographic characteristics during the survey collection period. When realized on different periods, with standards enabling comparing each survey with the previous and following ones, they also give access to travel behaviour changes over time regarding socio-demographic and terotechnological evolutions. At the beginning, transport modellers and researcher were the principle actors using this important amount of quantitative data. Public authorities have begun to realize the communicative power these could have, illustrating mobility's evolutions and policies efficiency. In the Paris Area, a focus group dedicated to mobility analysis – the Omnil – has made many EGT themed data sheets figuring the characteristics of the Paris Area. These data sheets deal with a variety of subjects such as Mode specific insights, Gender travel behaviour analyses, Week-end versus weekday and daily versus evening mobility, and Departmental mobility practices. Some of these are presented in Figure1.5.

Enquête globale transport

N° 14
Janvier 2013

La mobilité en Île-de-France

Modes

La marche

L'Enquête Globale Transport a été réalisée entre 2009 et 2011 et pilotée par le STIF en partenariat avec la DRIEA dans le cadre de l'Omnil. Ce sont 18 000 ménages (soit près de 43 000 personnes) qui ont répondu à un questionnaire détaillé sur leurs déplacements. L'ensemble des déplacements comporte une part plus ou moins longue de marche, par exemple pour se rendre à un arrêt de transports collectifs ou au lieu de stationnement des voitures. Cette fiche ne porte que sur les déplacements réalisés intégralement à pied.

La marche est le premier mode de déplacement des Franciliens

39 % des déplacements des Franciliens se font exclusivement à pied, soit un volume de 15,9 millions de déplacements par jour de semaine. C'est ainsi le premier mode de déplacement des Franciliens.

Les déplacements à pied
selon le lieu de résidence

	Nombre total*	Nombre moyen par personne et par jour
Paris	4,4	2,17/52 %
Cœur d'agglomération	6,8	1,60/43 %
Agglomération centrale	3,4	1,14/29 %
Autres territoires	1,3	0,94/25 %
Île-de-France	15,9	1,50/39 %

* En millions

La marche est le mode de déplacement de la proximité. En moyenne, la portée des déplacements à pied est de 430 m et leur durée de 12 minutes. En comparaison, pour l'ensemble des déplacements, la portée moyenne est de 4,4 km pour une durée de 24 minutes.

Adaptée aux tissus urbains denses, la pratique de la marche décroît au fur et à mesure que l'on s'éloigne de Paris.

Les Franciliens réalisent en moyenne 1,5 déplacement à pied par jour.

Enquête globale transport

N° 20
Janvier 2013

La mobilité en Île-de-France

Week-end

Les déplacements du week-end

			Transports collectifs		Voiture	
Samedi	3,33 déplacements par jour et par personne	35,3 millions de déplacements quotidiens	Une portée moyenne de 7,6 km	Une durée moyenne de 46 minutes	Une portée moyenne de 7,1 km	Une durée moyenne de 22 minutes
Dimanche	2,41 déplacements par jour et par personne	25,5 millions de déplacements quotidiens	Une portée moyenne de 8,4 km	Une durée moyenne de 51 minutes	Une portée moyenne de 7,5 km	Une durée moyenne de 23 minutes

Une mobilité individuelle plus faible le week-end que la semaine

Avec 3,33 déplacements par jour et par personne le samedi et 2,41 le dimanche, la mobilité individuelle des Franciliens est plus faible le week-end qu'en semaine (3,87 déplacements).

Les variations de mobilité selon le lieu de résidence sont nettement plus marquées le samedi que les autres jours de la semaine (cf. chiffres page suivante). Les Parisiens, qui se déplacent autant le samedi qu'en semaine, réalisent ainsi pratiquement un déplacement de plus le samedi que les habitants du cœur d'agglomération ou des autres territoires.

Comme pour les déplacements en semaine, l'usage des modes de déplacements le week-end est très contrasté selon le lieu de résidence. Plus on s'éloigne de Paris, plus la voiture occupe une place prédominante dans la mobilité des Franciliens. Ce phénomène est encore plus marqué le week-end que les jours de semaine.

Part de la population ne s'étant pas déplacée (le jour de l'enquête) : en semaine : 7 %, le samedi : 18 %, le dimanche : 25 %

Figure 1.5 – Omnil's data front sheet on walking and week-end mobility issued from the EGT 2010

Regarding the study phenomena in this research, household travel surveys are very valuable because the link that they enable between individual socio-economic characteristics and travel behaviours enables to study patterns between these, and to calibrate mobility demand models. It also enables to link mobility tools holding with mode choice and travel uses.

1.2.3 Other measurement instruments

Figure 1.6 proposes an organisation of mobility measurement instruments into several groups. This arrangement opposes automatically collecting data on individual mobility practices sensors to surveys revealing user preferences and practices. This distinction is clear as sensors collect data without interacting with travellers while surveys do. Within the sensor class, fixed, hybrid and mobile sensors are differentiated. Fixed sensors collect data on people or vehicle crossing a specific observed area. Hybrid sensors collect data on different spatial positions enhancing the observation range from fixed sensors. Last, mobile sensors can collect data following user movements, enabling getting data on whole origin-destination trips. Within the Survey class, field surveys are survey directly realized on the observation field when a surveyed individual is making a trip. Delayed surveys are realized afterwards when surveyed individuals have finished the trip and report it. Traditionally and because of the available technology, mobile sensors were not that much used for mobility measurement. Nowadays mobile instruments are being very competitive as GPS tools have spread through the population, enabling this source of data which is now cheaper and more complete than data provided by fixed sensors and field surveys.

In the remaining of this section, each mobility instrument is specifically analysed to highlight the information that it gives on mobility characteristics and its range of application to reveal user's mobility preferences and uses. First fixed and hybrid sensors instrument classes are described as counting instruments, then mobile sensors are dealt with, before detailing surveys mobility instruments classes.

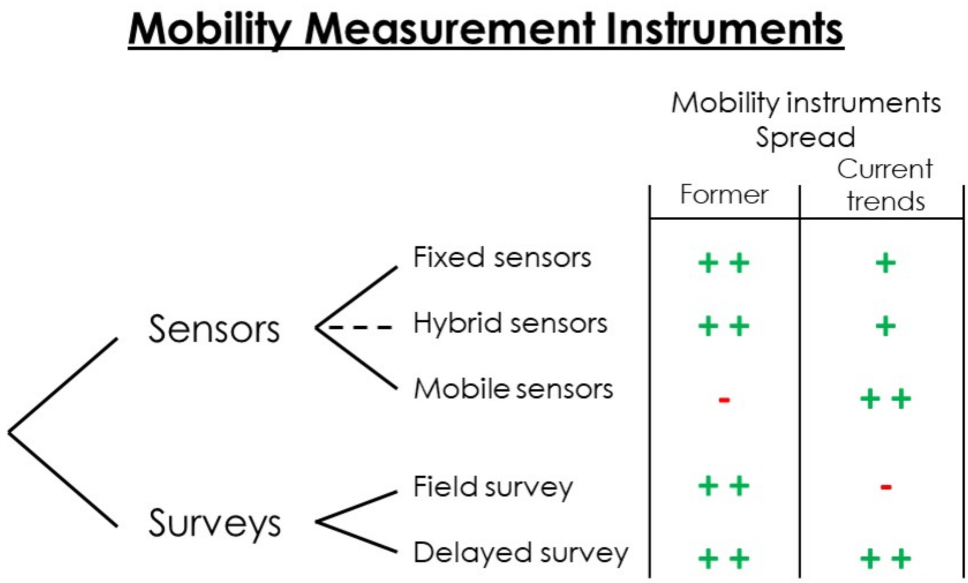


Figure 1.6 – Mobility measurement instruments categories

Fixed sensors

Fixed sensors can be fixed to a moving structure and are used to produce quantitative data. They mostly consist of highway traffic, intersection crossing or parking counting sensors. Traffic flows through specific places, quantities of moving objects sometimes dispatched by category, evaluation of densities can be obtained from these instruments. This section proposes a classification based on the mobility aspects that can be captured by the counting instruments considering existing classifications by Skszek (2001); Klein et al. (2006):

- Infrastructure embedded counting sensors: bending plates, inductive and magnetic loops, piezoelectric sensors, fixed ticketing devices, infrared sensors, microwave and acoustic radars,
- Movable counting instruments: movable infrared sensors, movable radars, pneumatic counting sensors,
- Video counting instruments: video cameras,
- Hybrid sensors: ticketing devices in buses, movable radars, unmanned aerial vehicles.

Fixed sensors offer the advantage that they can collect a high amount of quantitative data – number of axles, vehicles or persons, speed, headway and gap spaces value, weight, vehicle type distinction – on long observation periods. For embedded and video counting instruments, the data can even be accessible in real-time while the others collect data which is only accessible in delayed-time. Main limits of counting instruments come from the deployment and maintenance of the devices which are often expensive and from the device's own cost for movable counting instruments. Measure biases linked to the selected sensor or to the automated data processing can also occur, but they can usually be identified and controlled.

A specific focus on ticketing sensors is needed because that sensor type is not exactly like the others as it is an indirect sensor issued by validation systems. This sensor system enables tracking smart card data coming from subscribing to a PT pass or a pay-as-you-go ticket. The data on passenger's entry in the public transport system is collected in the validation system while the passenger's exit data is not always collected depending on cities and trips. When the data collection is centralized, this data set enables measuring public transit intermodal behaviours as each entry in the public transit is measured. Some public transit trips can even be rebuilt by crossing the different entry points such as in Kusakabe & Asakura (2014); Li et al. (2015); Pronello et al. (2018); Briand et al. (2017). This processing gives access to some mobility uses as shown in El Mahrsi et al. (2016) and is very useful for collecting data on intermodal trips, even though the exact trip origins and destinations are still unknown.

Socio-economic characteristics are also unknown but some can be deducted from the pass subscription category. Because this data is very sensitive and may enable identifying travellers, an anonymization process is usually conducted and delays the access to the data. The last issue comes from users without smart cards who are more difficult to track: final data sets are not exactly representative of the users' population even though they enable collecting a lot of data with very little costs as the infrastructure is first dedicated to validations.

Mobile sensors

Mobile sensors yield a lot of information on spatial localizations, enabling plotting trajectories from discretised spatial points and accurately identifying movement continuity. They are tied to a user or a vehicle which enables analysing individually disaggregated mobility data. Mobile instruments localization technologies characteristics are briefly described in order to better understand the data they have access to:

- Long distance mobile sensors: GPS (Global Positioning System) is the most used and accurate localization technology in an open field, with precision depending on the GPS commercial device, up to about 5m. It is not available on every mobile phone. GSM (Global System for Mobile Communications) is another very used but less accurate localization technology as it is available on every mobile phone. The communication signal is triangulated to locate the user.
- Middle distance mobile sensors of about 35m range: WiFi is available on smartphones with the connection to WiFi networks on. The phone automatically connects to the internet networks, leaving traces that are trackable and giving information on its position as WiFi radius are limited at about 35m depending on the WiFi area's spatial organization.
- Short distance mobile sensors of about 10m range: Bluetooth is available on most mobile phones with the connection to Bluetooth networks on. The principle is the same as for the WiFi.

As Ficco et al. (2014) states, the different mobile sensors are often combined to follow mobile traces in different environments. They enable studying outdoor and indoor trips with a space-varying accuracy. Mobile instruments' mobility measurement efficiency also thrives on the social aspect of smartphones and its diffusion in the population, and the intense development of computing capacities coupled with the increasing number of sensors embedded in smartphones has enabled increased functionalities capturing a lot of data. They can now be used to measure traffic flows in every places, full sets of temporal evolutions as a continuum, multimodality such as in Su et al. (2016); Shin et al. (2015), complete origin-destination trips analysis and many other personal trip data as in Gong et al. (2014). The data collection can also go on over a long period which gives access to the study of transport uses and trip purpose inferences such as in Xiao et al. (2016). The mobile instrument data use is increasing a lot as the data collection is based on devices owned by the surveyed population, highly decreasing the overall data collection cost. It now competes with fixed sensors and the more it spreads and develops, the more complete and accurate datasets mobile instruments give access to, the less counting instruments are used. Its main strength remains the access to classic counting instruments data plus deeper and more complete insights on transport uses.

The main drawbacks with mobile instruments data are the current technological detection and accuracy limits, and the fact that socio-demographic data can only be inferred and not established with certainty. Some data interruptions can occur and mode or trip purpose inferences can be wrong, introducing irregularities and errors in the data. The representativeness cannot already be ensured as the technological diffusion of smartphones mainly concerns young and active populations. Data privacy is also a concern because these observation methods are very intrusive. Even if the data is anonymized, information on a person's transport habits makes it easy to identify individuals. That issue could be mitigated with applications running under the smartphone's owner authorization only, but incentives to use such mobile applications are still to develop.

Surveys

Surveying is the preferred technique to collect qualitative data. It is conducted through interviewing or sending questionnaires to a sample of the population. When this sample equals the whole population, the survey is called a census. As they are realized in interaction with the user or the decision-maker, they can provide much information on mobility uses, purposes and behaviours. Surveys are usually subdivided depending on the methods of conducting the survey described in Stopher (2012); Transportation Research Board's Travel Survey Methods Committee (ABJ40) (2020) while this research proposes a classification based on mobility behaviours:

- Intercept field surveys made on the transport field studied, while respondents are experiencing a specific transport context. They are usually quick, localized and punctual. They enable analysing precise in situ user origin, destination and preferences to determine a service demand.
- Delayed surveys which can be realized everywhere and which collect user or interviewer reported preferences. They are conducted over areas and can

be repeated at different time intervals. They include census and Household Travel Surveys. They enable conducting more general analyses which can explore different contextual or non-contextual behaviours, with deeper understandings of users' motives.

The main advantage of surveys is that they give a direct access to socio-economic actors and their preference statements. Instead of relying on objective data they rely on perceived data which is important for understanding mobility perception and experiences. They give access to a very large spectrum of information as they can use open questions allowing the respondents to give a lot of detail with no other limits than the questionnaire's length. The mobility aspects that they enable studying include intermodality and social behaviours. The increased convenience of use of internet surveys has highly decreased questionnaire and survey costs diminishing the overall survey cost. Unlike other mobility instruments, surveys focus on mobility practices and behaviours, with not much information on traffic flows.

The main strength of survey techniques being the study of revealed or perceived behaviours is also its main limit because this data is difficult to verify and highly biased by contexts, by socio-psychological effects or by the survey method. Their cost is also growing with the questionnaire's length, the chosen survey instruments and the sample size. The measurement is conducted on limited space and time scales because of costs and respondents' memory reliability issues. Recent technology improvements enable survey developments using internet, phones or even simulation devices. Some projects have already proposed the use of simulations and avatars such as in Le Vine (2011) to try to overcome context biases, but they introduce other biases that might not be fully mastered yet. More generally, survey administration methods modify the context, and respondent attitudes are not the same for each.

1.2.4 Combining the different instruments

The different mobility instruments illustrate the variety of ways to approach and capture socio-economical phenomena such as intermodality and mobility tools holding, each revealing a piece of the global picture. The different mobility instrument's main advantages seem complementary for running a more complete mobility diagnostic. Crossing these methods together within the same study would multiply the possibility of analysis, definitely enhancing our understanding of mobility evolution and the interconnections among social, economic, statistical and physical aspects. The possible knowledge gains are numerous as such combination would help going over the classic time and space issues, enabling the fusion of qualitative and quantitative approaches on mobility practices recorded as a continuum over different spatio-temporal scales. It would also increase mobility study capacities as many more individuals would be reachable with an extended diversity of instruments.

Different categories of mobility actors are exploring this alternative. Metropolitan mobility planning authorities have many data sources available which they could better value. In the Paris region, Ile-de-France Mobilités is organizing the EGTand conducts additional stated preferences surveys, collects ticketing data and has also access to local counting instruments campaigns. Gathering all of this data into one general analysis would probably generate a better picture increasing the transport model calibration efficiency and the level of expertise on transport projects. As the mobile instruments data is getting cheaper, new directions toward buying additional mobile data to improve travel surveys as suggested in Cottrill et al. (2013) and explored in Bonnel et al. (2017) are being considered by many transport planning authorities over the world. Mobility operators are also interested by the potential power of this mobility instruments combination. They already have ready data on annual operating statistics, they have access to precise information on mobility dynamics, traffic flows and their link with services offer with regards to agents and vehicles management, and they regularly run origin-destination field surveys. They also possess many counting instruments such as safety video cameras and fixed sensors. The knowledge gains would help them optimize the services provision and enhance their understanding of crisis situations to better solve them. Patire et al. (2015) has already begun to couple mobile data with fixed sensors data to get a more accurate picture of traffic flows.

The challenges lie in designing automated ways to process this data in order to quickly give a big picture instead of relying on time-consuming manual qualitative processing. The main issue faced today is ensuring the compatibility of the different data formats especially regarding the overall errors and biases emerging from crossing datasets issued by different mobility instruments including different biases and errors. The underlying problematic is determining whether automated decision-making process could be implemented or if punctual combination is the only solution to getting a global picture of mobility at a metropolitan scale. Answers implying multi-source information systems based on already existing systems are being researched and some firms are trying to develop these solutions, paving the way for future real-time operation management and dynamic transport modelling.

Whatever the answers to mobility measurement problematic is, a hypervision of mobility is growing and is seen as a challenge faced by the whole transport community such as exposed in Bonnel & Munizaga (2018). Socio-diversity and geo-diversity have never been so well captured and developments are quickly arriving which gives the hope to get better understandings of transport behaviour and practices evolutions. The new mobility measurement techniques enable getting more data of improved quality which better describes mobility movement executions and traffic flows, helping calibrating the model and running more precise micro-economic modelling. transport authorities must follow the global trend to lead mobility measurement evolution, because they are progressively challenged by other entities which are collecting a lot of individual data and which already have algorithms crossing transport information such as Google Maps. The question of the role that modelling will play in this new setting is key for mobility planners.

With a more practical perspective, measuring the intermodality phenomenon is relatively complex because it involves several transport networks with different measurement instruments. Because of this diversity of transport networks, it is a phenomenon which would clearly benefit from a combined approach of mobility instruments. This would help better assessing it, instead of only relying on HTS data, which always have some biases and errors because they are stated preference and not revealed preference observations.

Conclusion

After discussing the importance of the field and administrative governance analysis to conduct mobility analyses, this chapter has emphasized the structure of the mobility system around the mobility system supply, demand and uses. Key mobility and socio-economic indicators have been highlighted. Yet these indicators are measured through different processes, and the different mobility measurement instruments have been presented to better understand their utility and their limits. The case of household travel surveys is probably the most important one as it is the main data source for the remaining of this dissertation because of the high value of combining socio-economic and travel behaviour observations.

This chapter has set up the basis for an analysis of mobility tools holding and intermodality at the metropolitan scale, with a detailed field description summary for the Paris region study case. The Paris region has a mobility structure enabling mobility services innovation thanks to as strong PT frame and the development of many motorcycle, bike and scoot services in the recent years.

From this general Paris region mobility analysis and understanding of mobility measurement tools and concepts, the remaining of the dissertation aims on finely characterizing mobility tools holding and intermodality while accounting for field and indicator specificities highlighted in this chapter. It also discusses the potential for integrating these mobility phenomena into well established mobility demand models.

Chapter 2

Mobility Explanatory Power of Travel Demand Models

Introduction

While chapter 1 rather is a chapter describing the thematic background of this dissertation, this chapter focuses instead on the methodological background from the travel demand modelling field of research. Indeed, well understanding the main principles on which mobility planning is built helps analysing its current limits and its unexplored potential.

Modelling metropolitan mobility systems at a spatial scale encompassing an urbanized area and its attraction basin of related settlements is strategic to evaluate metropolitan development projects as well as transport master plans. The so-called Travel Demand Models (TDMs) model demand in interaction with modal networks. As Batty (2009) details, they aim to replicate preconceptions and observations of mobility in order to quantify its evolution, which enables testing projects or policy scenarios by providing traffic estimates and a large range of social, economic or environmental impacts. This chapter focuses on briefly presenting TDM modelling tools used to establish transport master plans, and on comparing operational Paris transport models to better understand their main features, in order to be able to build an analysis frame assessing the mobility explanatory power of these models. This is also the occasion the discuss how mobility tools holding and intermodality interact with the current theoretical modelling framework.

In Chatzis (2015), a history of the development of the travel demand models and their penetration within the French transport sector gives an overview of the set up of travel demand models as major methodological tools to study metropolitan mobility. Three main periods can be distinguished in the travel demand model history, associated with different socio-economic paradigms and model theory priorities.

A first period between the 1950s and 1980s begins with the apparition of the first traffic models in the 1950s, and the birth of the discrete choice theory with McFadden (1974) in the 1970s. This period was characterized by a development of the urban and interurban transport infrastructures, coupled with a rural flight and strong urban growth. These developments were based on two main modes in France: the rail and the car, so models were built to forecast the demand for new rail or road infrastructure, in order to increase the transport supply. This demand has a spatial component that has begun to be addressed in the 1960s with Voorhees (1959), limited by the computation power available at the time.

The second period happens between the 1980s and the 2000s, with the disenchantment regarding the car-based urban transport mode, and the need to balance the car modal supply with PT. While the traffic assignment models used to be built for car, PT assignment models begin to be implemented too. The policies driven by transport infrastructure growth are also questioned and becoming less popular. The discrete choice models evolve to account for more choice alternatives. The environmental concern also rises in the 1990s, and new environmental modules are developed to convert transport flows into emissions The concept of transit-oriented development favouring PT use also becomes a major focus of the transport research community. It can be seen as a shift from traditional transport economic models, to transport socio-economic models.

Since the 2000s, the third period has begun. It focuses on the mode and travel diversity, and especially the promotion of active modes. From monomodal trips, the trips are now multimodal and intermodal. Ownership models begin to focus on other equipment than the car, and the model theoretical structure begins to be more complex to reflect the increased complexity of the transport system. This corresponds to a shift from transport socio-economic models to mobility systems models. With the increased computational power, joint land-use and transport integrated models also become more accessible. Even though models have evolved, it still remains to identify whether this technological evolution matches the ambition of the mobility phenomenon representing, and how this impacts operational mobility planning.

In order to provide answers to this last point, base concepts of mobility modelling are considered within the perspective of highlighting how they deal with representing mobility. The theoretical modules involved in mobility modelling are described and analysed under this perspective of discussing what mobility process they estimate. This chapter does not aim on challenging the mathematical formulations, but on displaying the general hypotheses behind these. As models are simplifications of reality, their limits are also put forward. After understanding the theoretical spine of the models and the most common model categories, it is possible to describe Paris operational models under the scope of the mobility phenomenon explanatory power. An analytical tool is also set up to enable quickly understanding this mobility explanatory power, and to compare models with different technological bases, regarding this mobility explanatory power.

This chapter first describes the traditional model concept based on the four step model, by detailing the different steps articulation and presenting each step's contribution to explaining mobility. It then provides a general comparison framework to enable the comparison of diverse models and to better display the way they represent mobility. This framework is based on a systemic economic analysis. The analysis grid built is applied to Paris region models in turn ranging from classic four step models to more complex tour-based models. A final summary table is drawn as synthesis and benchmark providing stem directions of improvement for each model. This synthesis highlights TDMs differences and the consistency between their structure and the operational needs. The comparison analysis from section 2.2, 2.3 and 2.4 comes from the communication Trouve & Leurent (2018).

2.1 The Traditional Modelling Concept

Metropolitan mobility modelling theory is based on the four step model structure developed in the 1970s. Even though this structure is not recent and its former use with aggregated data is not very common anymore, most of the new models are developed from this initial scheme or can be related to it. This section aims on describing the characteristics of this classic model characteristics which are further detailed in Bonnel (2004); Ortùzar & Willumsen (2011), to enable better understanding of the travel demand modelling field of research.

As its name suggests, the four step model is articulated around four main steps: the trip generation, the trip distribution, the mode choice[1] and the assignment. An adaptation of the classic four stage articulation scheme appears in Figure 2.1 to graphically display the four step model's structure. Based on observed data on the base year mobility supply and demand equilibrium, and on some future data matching scenarios to evaluate, the modelling process is conducted to estimate trips emitted and attracted by each zone unit, trip flux between zone units, mode shares and traffic flows.

- First, the generation step models the number of zone, household or individual trips emitted and attracted by analysis zones. The result of this step is an emission matrix and an attraction matrix detailing the number of emitted and attracted trips associated with each zone.
- Second, the trip distribution step enables to build Origin-Destination(OD) flux by combining the previous emission and attraction matrices. It connects each emission zone to several attraction zones and results in an OD flux matrix detailing the number of trips connecting each zone OD pairs.
- Third, the mode choice step builds on the previous OD flux matrix and aims on spreading the flux among the several transport modes encompassed in the study. This step's output is an OD flux matrix for each of the considered transport modes.
- Fourth, the assignment step aims on dispatching the trip flux on the associated transport mode network in order to get the route selected to make each trip and compute traffic flows. For each considered transport mode network, this step dispatches the input OD flux matrix into matrix flows on each of the network links yielding a final matrix of network traffic flows by mode.

[1] called Modal split in Ortùzar & Willumsen (2011)

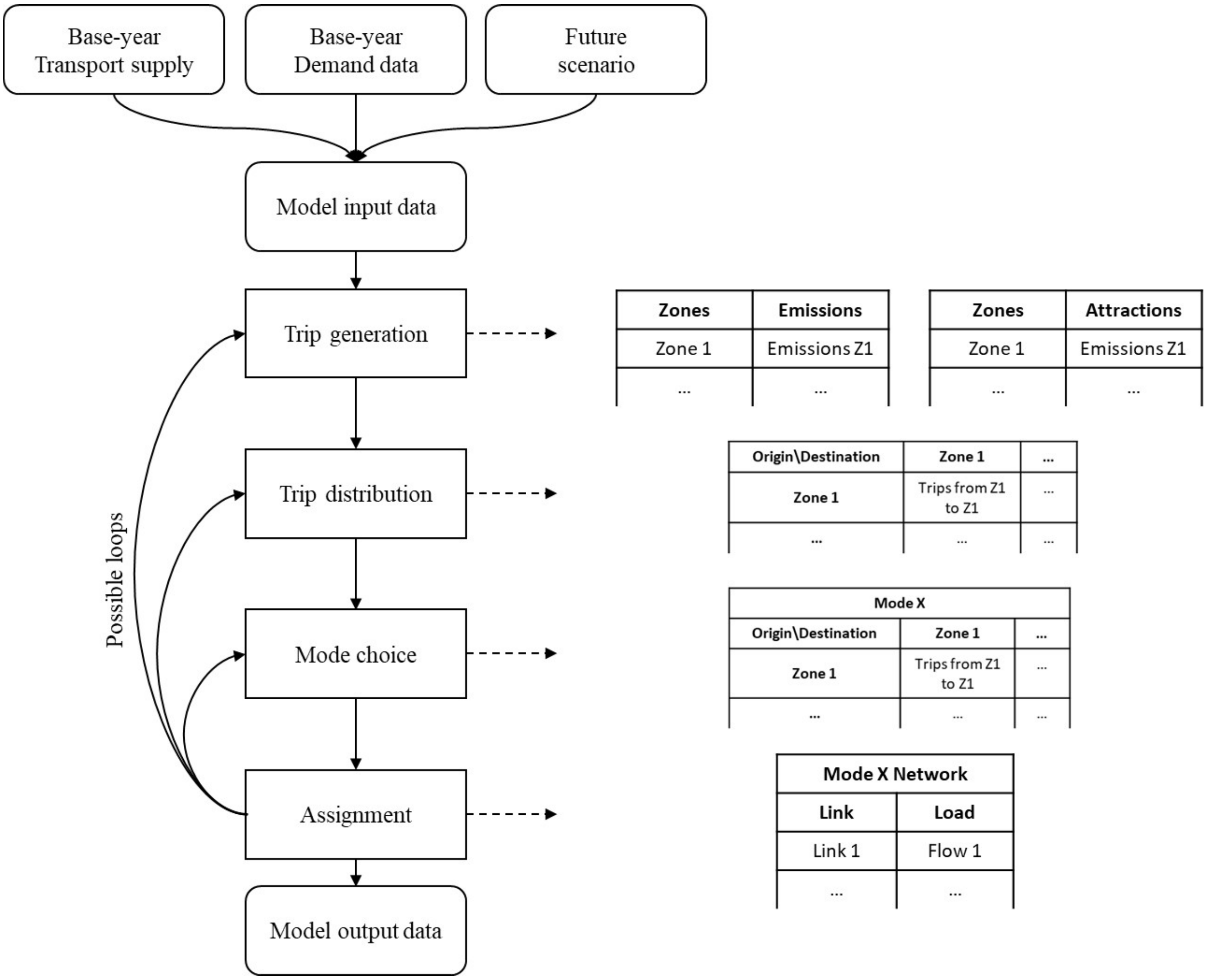


Table 2.1 – Adaptation of the classic four stage transport model from Ortùzar & Willumsen (2011)

Because most of the explanatory variables come from land-use characteristics, several Land-Use and Transport Integrated (LUTI) models have been set up to endogenise these variables. This is made by implementing another step zero modelling urban development. The final model output traditionally is traffic flows on the road and PT networks, which can be converted into GreenHouse Gases (GHG) emissions by adding another final module linking the traffic flows to GHG emissions levels with average vehicle consumptions. This enables to adapt the model to evaluate the environmental impact of transport projects. Depending on the study, the output can then be flows, mode shares, number of trips, emissions, OD matrices or any item related to these.

This modelling structure might seem robust to estimate traffic flows at first, but it has many flaws. The first and probably most important one is that the results of the later step impacts the former steps: for instance, it is irrelevant to suppose that the final traffic flow conditions do not matter on the other previous steps. More explicitly, if running the model once shows that every individual is taking the car to make their trip from a certain zone, this will probably yield very congested roads around the studied zone thus deteriorating the car attractiveness which would reduce the trip emissions directly impacting the trip distribution, and the car mode. A solution to this general issue is to implement a loop on the model so that the results of the first model iteration change the inputs to conduct a second iteration and so on until convergence toward a stable equilibrium. A consequence is that models without loops do not ensure consistent results. Even though practical to run the model, this model structure does not always match the trip-making choice process, and so the second most common issue probably comes from the steps sequencing that is addressed in many ways in the literature.

After this general description, the remaining of this section focuses on briefly describing each step of four step models, before a last subsection presenting its limits and more recent models mostly developed from this initial approach.

2.1.1 Trip generation step

In order to estimate the trip emissions or attractions, several approaches are possible. The most usual ones are exposed in this subsection. First, the definition of accessibility indicators enables to link the following steps with the trip generation. Second, two main modelling techniques widely spread in the field are presented: growth factor and multiple regression.

The principle of accessibility indicators is to build a variable accounting for the easiness or difficulty to reach a zone. Accessibility indicators can be computed for each zone and for the whole population, or they can be dispatched among several disaggregated accessibility indicators linked with individual attributes. For example, computing the number of network links reaching a zone could feed a general zone aggregate accessibility indicator, while more detailed travel times characteristics depending on an individual physical ability could feed individual disaggregated accessibility indicators. The choice to use disaggregated or aggregated accessibility indicators is mainly determined by the data available and the decision-making unit analysed. Aggregated accessibility indicators have the mathematical form:

$$A_i = f(\mathbf{C}_i) \tag{2.1.1}$$

where A_i is the accessibility indicator for zone i, $\mathbf{C}_i$ is a vector of connectivity characteristics of zone i, and $f()$ is a function to determine. Disaggregated indicators require to add some disaggregated variables and their formula is slightly different:

$$A_i^n = f(\mathbf{C}_i^n) \tag{2.1.2}$$

where A_i^n is the accessibility indicator of zone i for the disaggregated unit n, $\mathbf{C}_i^n$ is a vector of connectivity characteristics of zone i for the disaggregated unit n.

A spread disaggregated accessibility indicator formula reproduced from Ortùzar & Willumsen (2011) is:

$$A_i^n = \sum_j E_j^n exp(-\beta \times GC_{ij}) \tag{2.1.3}$$

where E_j^n is a measure of the attraction from zone j for the individual n, β a parameter to estimate and GC_{ij} the general cost for travelling between zone i and zone j.

Incorporating travel time characteristics that are modified by the last step of the model in the accessibility indicator enables to refresh the generation step with actualized data and to make this indicator dynamic.

But this indicator does not explain how trips are computed by itself. A historical approach was to set up economic growth factors. The principle is to build a growth factor by witch the reference year's number of generated trips is multiplied to estimate future trip generation. The equation describing this process is:

$$t_i^{t_0+t} = F(t)_i \times t_i^{t_0} \tag{2.1.4}$$

where $t_i^{t_0+t}$ is the estimated trip number for at time $t_0 + t$, $F(t)_i$ is the growth factor for zone i and a time period t, and $t_i^{t_0}$ is the observed trip number at the reference time t_0. The building of $F(t)$ is key for this estimator's efficiency, and it is generally considered as a function of socio-economic characteristics such as population, income, number of jobs and so on. Usually, growth factors follow the scheme:

$$F(t)_i = \frac{f(\mathbf{SE}_i^{t_0+t})}{f(\mathbf{SE}_i^{t_0})} \tag{2.1.5}$$

where $\mathbf{SE}_i^{t_0+t}$ is the vector of expected socio-economic variables for zone i at time $t_0 + t$, $\mathbf{SE}_i^{t_0}$ is the vector of observed socio-economic variables for zone i at time t_0, and $f()$ is a function to determine.

This estimator is not very precise and can yield wide variations but it enables to get forecasts even with only a few data available. It is now usually replaced by multiple regression estimators enabling to add an intercept variable capturing variations not associated with dependent variables, which can be linear are non-linear.

So this step enables computing both trip emissions and attractions through these general methods. But the final result does not ensure that the total number of emitted trips equals the total number of attracted trips. In order to solve the issue, one of these two trips must be adjusted to the other. Trip emission estimators are generally more refined as they have several individual variables descriptors, while it is less the case for attraction estimators. Based on this statement, trip attractions usually are scaled to the trip emissions total: they are multiplied by a factor equal to $\frac{TotalEmittedtrips}{TotalAttractedtrips}$.

The efficiency of the trip generation module is tightly linked with the geographical description of the metropolitan area in the models. Traditionally, the continuous geographical space is divided into zones. This cutting procedure has strong impacts on the model results, based on the number of zones considered and the way the cut is made. For instance, getting more zones is considered as a model improvement as it gives a much more precise description of the metropolitan area. But increasing the zone number is not enough to ensure a greater efficiency, the cutting must respect geographic homogeneity and highlight geographic heterogeneity. As for clustering procedures, the trip generation efficiency is directly linked with the cutting process and scale.

After this technical description of the module, it must be assessed regarding the way it describes mobility. While the approach of linking trip emissions and attractions makes sense at the aggregate scale when it is reasonable to consider that a zone trips are linked with its demographic and economic features, it does not stand at the disaggregated household or individual scale. Indeed, it seems less valid to evaluate trip emissions from household income for instance. Conceptually, this step is also disconnected from the mechanism of trip emissions and attractions: an individual generally makes a trip to reach a place where she can carry out a specific activity. Within this scheme, it seems more relevant to consider trip emissions and attractions depending on activities.

While economic and demographic characteristics are indicators of an activity potential at the aggregated scale, it is not any more the case at the individual scale. This observation is challenging as applying it fully means that the lower the scale, the less the trip generation modules is accurate. This statement is directly opposed to the previous one encouraging much detailed spatial resolution to increase the model efficiency. So the trip generation procedure fits well aggregated modelling for low spatial resolution, but it must better account for activity patterns with a more detailed spatial resolution.

With a mobility planning perspective, this steps also gives more importance to high population and rich areas than others. Considering that these models have first been used with a pure transport infrastructure development objective, this module tends to give more importance to rich and populated central zones, fostering centralization and geographical inequalities.

2.1.2 Trip distribution step

Now that trip emissions and attractions are available, the distribution step connects the attractions to the emissions to yield an OD trip matrix.

The first methods used to compute these matrices are similar to the generation step: from an observed OD matrix at a reference time, economic growth factors are computed to evaluate the future OD matrix. This growth factor method can be aggregated for all trips or disaggregated for each OD pair, depending on the data availability at the zone or overall scale. This process again rises the issue of equal emissions and attractions for each origin and destination. Single constrained growth factors can be set up by implementing origin coefficient to scale the attracted trips to the origin trips. Reciprocally, it is possible to set up a destination coefficient. Eventually, a last double constraints solution is possible when a large data set is available for the origin and the destination growth factors but requires simulation to estimate the scaling factors. But as previously, these growth methods are not recommended for long-term forecasts or for forecasts with a lot of variable changes as explained in Ortùzar & Willumsen (2011).

The most spread out method for the distribution is the gravity one. According to Isard (1954); Bonnel (2004); Ortùzar & Willumsen (2011); Isard (1954), it comes from an analogy with physics and the famous Newton gravitation law describing the attraction between two bodies, which intensity is linked with the weights of the two bodies, the squared distance separating them and the gravity constant. The analogous reasoning built for the trip distribution is to consider that the intensity is the number of trips for a specific OD pair, the weights being the number of emitted trips from the origin, and the number of attracted trips to the destination, the distance being the generalized cost of traveling from the origin to the destination, the last constant remaining to determine. The final equation proposed in Ortùzar & Willumsen (2011) is:

$$T_{ij} = \alpha \times O_i \times D_j \times f(c_{ij})$$

where T_{ij} is the number of trips from the origin i to the destination j, O_i is the total number of emitted trips by i, D_j is the total number of attracted trips by j, c_{ij} is the generalized cost of travelling from i to j, $f()$ is a function to adjust but which should be decreasing with high general costs, and α is the coefficient to determine also carrying the constraints. Indeed, the proposed formula does not immediately offer a solution to keep the total number of emitted trips and attracted trips steady. Several methods exist, similar to these from the previous step.

Another distribution method is the entropy formulation also described in Bonnel (2004); Ortùzar & Willumsen (2011). Without fully detailing its mathematical formulation, it considers that the overall number of trips or the emission and attraction matrices are a macro state, that each OD flow is a meso state and that individual OD trips are the micro state. It assumes that the micro states is mostly unknown and a generic micro behavioural probability law is assigned, but that values of the meso state can be computed from constraints – e.g. equal number of emissions and attractions per zone – set by observed values of the macro state, and from former observations of the meso state – i.e. former OD matrices –. The aim is then to optimise the micro state probability law to increase the likelihood of reaching the observed meso state while not breaking the constraints.

Last, more recent models even use discrete choice models at this step while these were traditionally developed for the following mode choice step.

This step is probably the one which is the most disconnected from the mobility phenomenon one, because it mostly is an assignment procedure not directly accounting for socio-economic effects. It matches different producers and consumers together, without accounting for specific relationship between emission and attraction zones. A more relevant approach at the aggregated scale would be to consider the zone activity mix, and to give more weights to trips going to a zone with activities different from the emission zones, which echoes to the theoretical opportunity model not much practically applied according to Bonnel (2004).

With a disaggregated perspective, travellers do not chose destinations while ignoring their origin point. The origin-destination choice is encompassed within the activity choice and simultaneously made instead. Other issues related with the zoning applied and the gathering of all the trips in the centroids artificially takes away or brings closer origins and destinations which are around a zone border. The definition of $f()$ is also very important and sometimes to general as it supposes similar decision structure for every zone.

Similarly with the previous step, the trip distribution highlights connections between the most wealthy and rich zones, focusing on the effect of few structural transport axes. Indirectly, this amounts to lowering the interest in the other zones which end up being less connected when mobility development is purely based on models.

2.1.3 Mode choice step

Getting the number of trips per OD pair is important for policy makers because it enables assessing the overall demand for transport. Yet, this demand is aggregated and does not show how different transport mode perform against each other. This modal disaggregation is made through the mode choice step which aims on dividing the OD trip matrix into OD trip matrices for each mode.

This step's development in the second half of the XX^{t}h century is probably one that contributed the most to travel demand models development at the time. Discrete choice models are briefly described in Ortùzar & Willumsen (2011), and more detailed in Ben-Akiva & Lerman (1985) with more recent applications proposed in Train (2009). Based on the socio-economic characteristics of the trip-making unit, the general trip characteristics and the trip characteristics associated with each mode, discrete choice models enable a statistical estimation of the probability of choosing among several modes.

In order to compute these probabilities, the principle is to give a utility score to each mode. This score is made of a systematic component built with the observed characteristics converted into independent variables, and a random error term capturing the unobserved characteristics and the randomness of the choice process. Each utility is ranked against each other, and the highest one has the highest probability of being picked. The probability computation relies on a hypothesis on the error term distribution. The most common one has been the logistic distribution because it has an easily accessible closed form expression not requiring simulation. The second one is the normal distribution which requires simulation with a high number of alternatives, but which enables to implement some taste variation parameters in the distribution. The basic formula for the most common multinomial logit model is:

$$U_{i,m} = V_{i,m} + \varepsilon \tag{2.1.6}$$

$$P_i(m) = \frac{exp(V_{i,m})}{\sum_m exp(V_{i,m})} \tag{2.1.7}$$

where $U_{i,m}$ is the utility of choosing the mode m for i, $V_{i,m}$ is the systematic utility component built as a function of independent variables describing the choice-making unit i, and of the trip characteristics when made with mode m, ε is the error term, $P_i(m)$ is the probability of choosing mode m to make the trip for the choice-making unit i.

The main limit of the traditional multinomial logit model (MNL) is the independence of irrelevant alternative (IIA) property stating that each choice alternative must be independent from the others, while the error terms always have some degree of dependency. These models have since improved a lot and many papers have presented new techniques such as nested models, ordered models, cross-nested models, mixed models, latent choice models or discrete-continuous for instance. This list mostly comes from different error terms distributions enabling patterns of error correlations. It is not exhaustive, and is still expanding.

The mode choice step is also the result of an approach initially assuming fixed parameter values for the whole population. It means that having a higher or lower income would have the same effect as for the distribution step on the whole population regarding the mode choice. Even though it is possible to include other variables to reflect differences issued by measurable socio-economic variables. Some mode choice models offer the possibility to distribute variable parameters around a mean, with a standard deviation value, which is the main interest of probit formulations. But the remaining general approximation, and individual taste differences are always difficult to model, especially as the mode choice structure may even change among individuals and trip activities.

At the opposite of the first two steps, this one has been designed at the individual scale, so it performs well with disaggregated approaches, and is easily transferred to more aggregated approaches.

The main issue of this module regarding the mobility phenomenon representing is that it considers that the choice is always made depending on objective factors. As such, it overestimates the potential mode choice changes for usual trips. Reality suggests that usual trips are perceived as habits, and that mode choice changes for these trips happen after disruptions or life events. The definition of the utility function and of the choice structure is very often generic and not flexible enough to display the diversity of individual choice-making processes and structures.

2.1.4 Route assignment step

The last route assignment step aims on assigning the OD modal matrices to the corresponding modal networks in order to evaluate individual and vehicle flows. This assignment is made through a graph simulation representing intersections as nodes and roads as one way or two ways links depending on the number of directions for the road. Several assignment methodologies are presented in Leurent (2006) with applied examples.

From the graph representing and existing transport network, optimization algorithms enable computing trip characteristics depending on the origin, the destination and the link characteristics. The traditional algorithm used for this assignment is the Dijkstra shortest path finding algorithm. The first method has been to assign the route with the lowest travel time which often makes sense because individuals are not commuting for the pleasure of travelling but to reach places. An alternative to this method has quickly been to consider generalized costs instead of travel times only: instead of trying to minimize the travel time, trip makers also consider the costs of the different routes, which are mixed together into a generalized cost. This approach is relatively diffused and enables conducting pricing and value of time studies.

From these first methods, two remarks have arisen: generalized cost is a fine approach, but the value of time is not the same for every individual, and it is not valid to hypothesize that everyone has the same general cost perception; and that not every individual has a perfect knowledge of the network and will actually chose the most desirable alternative, but would rather chose the best one she knows of. These can be considered by implementing individual characteristics and error terms with distributions in the generalized cost formula. This amounts to adding stochastic effects within the model.

A main contribution of the assignment step to the model is when it accounts for congestion. This translates to considering that each network link has a limited capacity depending on its ability to carry several individuals or vehicle at the same time. This capacity is linked to the maximum speed on the link as congested links where the capacity is almost reached have reduced speeds following a capacity and speed fundamental diagram principle. From these, assigning travellers to the link reduces its speed and modify its average cost. So a loop procedure can be implemented to reflect the impact of assigning individuals to a route on the generalized cost. Yet the convergence is not always ensured, so several techniques have been developed such as incrementally assigning fractions of the overall demand. When this congestion constraint is considered, the assignment model is an equilibrium model.

But this assignment procedure rather fits modes which are immediately available. When studying the PT route assignment, this process is not any more well adapted. Instead, a line network representing the different PT lines and their connections, their average headway and so on. Indeed, these will represent the different characteristics of the PT supply displaying waiting times at different stations. Some more complex PT assignment even consider another mission layer where each PT vehicle belongs to a mission and can disturb another vehicle if the loading or unloading time is too important such as in Poulhès et al. (2017).

The main issue with assignment models regarding to mobility representing is that they are based on mathematical optimization processes which highly value small differences. So for instance, an assignment procedure assigns the route with the lowest value, even when there are five different routes with generalized times differing only by a small fraction which is not even perceived by the trip maker. This issue appears with real-time route assignment software which often advise to use itineraries involving small roads to be a few seconds faster, while not really worth the effort of leaving and joining again the same main road for instance. Technically speaking, the convergence of the assignment models can be an issue when not enough constraints are applied.

2.1.5 Limits and extensions of the traditional model

This quick description of the four step model shows how it deals with mobility: it considers that some socio-economic factors are behind trip generation for different zones which are then connected together during the trip distribution. These trips are next divided into different modes before being assigned on a network. Even though practical for modelling purposes, it does not seem to well represent how the mobility decision is taken by individuals. This is all the more valid with new behaviours linked with available mobile phone technologies, with which the final destination of a trip is not always known before beginning the trip. Aside this structure which does not suit every mobility decision, it also only focuses on the mobility mode choice and use, without endogenously integrating other decisions tightly related to this mobility decision equilibrium such as the availability of mobility equipments or the urban development.

The scale on which the model is used also has some importance on its meaning. When the first four step models were developed, it was on aggregated data with information on average distributions of attributes within zones, to study car and PT modes only. With the spread of travel surveys and the increase of the number of respondents to conduct more detailed and robust statistical analyses, the metropolitan models generally are built on disaggregated individual data nowadays. While a mobility decision structure very approximate on aggregate data might still fit aggregate decisions, it is less valid for disaggregated data more related to the individual decision. So this traditional four step model, even though having heavily contributed to the field of travel demand, is not any more adapted for analysing current mobility challenges and must be expanded and transformed.

A last generic limitation to any model is the quality of the input data, and the definition of the mobility system as presented in the previous chapter – e.g. definition of the spatio-temporal frame –. These remarks are general on the concept of the four step model. Going into more details, it is also possible to challenge each of the methodologies used for each step, but the goal rather is to question the conceptual frame of the four step model rather than its technical implementation.

In order to answer these challenges, several responses have been proposed. First, each step's methodology has improved and many formulations now exist. Second, the models which used to be general for the whole population are now more often dedicated to specific population segment. For instance, it is not unusual to have one model dedicated to men's mobility while the other is dedicated to women's mobility in order to display mobility gender inequalities. This is different than adding a gender dummy variable in a model, as it implies different model parameter values for each segment. Within this trend to disaggregate the four step model into segments, a new model type has appeared: the activity models dedicated to different activities. These especially enable to observe different mobility behaviours depending on the trip purpose which can often be dispatched among mandatory and optional motives. Generally mandatory trips are the home-work and home-study trips while optional trips are leisure trips. The status of grocery trips is not always clear as they are mandatory in a sense, but generally are not as constrained as work trips.

The next improvement following this segmented activity modelling approach is the tour-based modelling. These models do not deal directly with trips but with tours as it is hypothesized that the trips are organized within tours which constrain the trip making. Indeed, when making a tour, the choices made on the outbound trip generally have implications on the inbound trip. For instance, taking a private car or a private bike to do some grocery shopping often implies taking it on the way back home. Similarly, not taking a private vehicle during the outbound trip implies that it is not available on the corresponding inbound trip. The tour approach enables conciliating the inbound on outbound trip making decisions, but requires disaggregated data while the previous models could be built on aggregated data.

The last improvement also focusing on micro-economics is the multi-agent approach, where each individual is modelled with its own decision process dynamically affected by the decisions made by other agents. This modelling, even though very detailed, requires a lot of data and computing power. Yet, it can yield very precise scenario characterization. The main obstacle to its development still is the computing power and data availability, but these two fields are quickly evolving.

So far the discussed improvements mostly were about the mobility segment and object. Other models propose instead to expand the mobility analysis with other mobility-related phenomena. The most developed category of such models probably is the Land Use and Transport Integrated (LUTI). These theoretical models not yet much operationally used endogenously represent land-use development and mobility within the same model environment. This enables more in-depth studies of the relationship between both phenomena.

A remaining point is the fact that these models are often overestimated and decision makers often consider them like forecasting tools. The whole mobility modelling field is based on one main principles: data is collected for a base year, in order to calibrate the model. The model "forecasts" are made by applying these calibrated parameters on the population socio-economic projections input. So mobility models just replicate observed mobility behaviours on population projections, and are not a proper forecasting tool. As such, they are unable to estimate the effects of new modes or new mobility behaviours from another socio-economic paradigm. Stated Preferences(SP) surveys can be conducted to calibrate these models for fictive socio-economic and mobility settings, but they include several survey biases. Some manual manipulation can also be made to adjust models to account for some changes, but it is important to remind that models still have this limit. Considering this point, models are still not well structured to account for intermodal trips and growing mobility services subscription effects.

After this section describing the travel modelling concept, the next section focuses on developing a comparison frame to assess the existing operational model in the Paris region.

2.2 Model Assessment Framework

Most of the recent literature on transport models comparison is divided between operational model comparisons and theoretical model comparisons while TDM results comparisons is not very spread in public academic research. But operational models comparisons often focus on transport models dedicated to one aspect of mobility and not to overall metropolitan transport models, such as car ownership or freight transport models. Second, theoretical models comparisons are often limited to specific transport models such as LUTI models.

The review of car ownership models in de Jong et al. (2004a) displays many different cases and gathers more than thirty-three different models into nine model classes. The comparison is based on sixteen criteria clearly reflecting the different aspects included in each model class. A more recent research described in Anowar et al. (2014b) provides another interesting framework proposition for automobile ownership model comparisons based on the dynamic/static and the endogenous/exogenous aspects of the models. Moreover Shaygan et al. (2017) also proposes a car ownership model comparison, but based on the different urban environments they are applied to, enhancing the metropolitan characteristics of the field where the models are applied and nurturing international model comparison.

For freight transport modelling, de Jong et al. (2004b) build an analysis detailing the methods used on the different steps of four step models providing practice use cases and development propositions. This classification is interesting but does not facilitate comparing metropolitan transport models that are not following the four step model scheme. On a less detailed approach, Tavasszy (2008) links the decision problems encountered by freight modelling to modelling challenges and the general modelling techniques used to answer these challenges. Chow et al. (2010) improved this approach by providing a table showing the policy decisions that each model type is best for answering at. Freight modelling approaches are theorized in the handbook Tavasszy & de Jong (2013).

In order to establish a LUTI model comparison, Wegener (2004) first distinguishes eight metropolitan systems that are mobility choices ranging from long term choices to immediate choices. This modular decomposition of the mobility phenomenon is structuring and supports the consideration of mobility models as an interaction of different mobility modules each dealing with different mobility sub-phenomena. Models are then ranked according to their way of integrating the different choices faced by individuals. Yet it does not build many criteria for comparisons and it does not draw a summary table synthesizing the analysis and confronting the models. Hunt et al. (2005) pushes the exercise further with a detailed way of addressing the phenomena represented in the LUTI models and their treatment in the model. Batty (2009) takes a different approach opposing LUTI models class to urban dynamics models class and to cellular automata, agent-based and microsimulation model class. This last approach focuses on technical modelling solutions that are not the core of this research as it does not reflect the mobility aspects integrated in the models.

To conclude this review, there is a lack of accessible recent literature about metropolitan transport models classification and comparison aiming at showing the essence of the models and their global consistency, even though some interesting comparison frameworks can be found for more focused operational or theoretical models, especially for LUTI models such as in Hunt et al. (2005).

2.2.1 General framework

A first step before building the grid is to understand why there are several model types that have appeared while the TDM building is rather standardized by the handbooks Ben-Akiva & Lerman (1985); Bonnel (2004); Ortùzar & Willumsen (2011) on the academic side, and by institutional guidelines such as the United Kingdom's WebTAGs on transport modelling. These standard frames rely on a dispatching among three blocks: Supply, Demand and Uses. That structure is therefore found within every model the authors have encountered so far. The model customization by different entities comes from a different way of building each of the blocks. In order to represent every models and how they are customized by each entity, the aimed grid should be organized around the main blocks and detailed within so as to explicitly show models divergences.

To reach this objective, the analytical framework proposed in this dissertation is built around four main criteria blocks from the transport economics structure: the definition of a spatio-temporal frame, the demand block, the supply block, and the meeting of both demand and supply with the uses. The framework details these blocks with 22 precise criteria in order to show its structure, the mobility behaviours considered and the articulation with the other blocks such as the modalities of the feedback from the uses to the demand and supply blocks.

2.2.2 Spatio-temporal representation

The spatio-temporal frame representation block defines the perimeter and the level of accuracy of the model. It is divided among 5 criteria:

- The *analysis unit* details whether the model decisions are made at individual, trip or tour scales,
- The *zone modelling* details the number of Traffic Analysis Zones (TAZ) in the model and the average surface and population encompassed in one TAZ. This criterion illustrates the spatial granularity of the model,
- The *external demand modelling* details the treatment of the demand out of the spatial framework such as touristic or professional travels and travel to or from neighbouring territories,
- The *time period modelling* details the periods of the day represented,
- The *departure time modelling* details the ways the demand is affected among time periods and whether modifications of departure times are considered.

2.2.3 Demand representation

The demand representation block identifies how the demand is generated with the general choice structures, the demand segmentation, the implementation of constraints, and the different specific demand characteristics considered. It is divided among 9 criteria:

- The *mobility choices modelling* details which choices are modelled ranging from long-term choices to immediate choices: residential location, travel, mobility tools ownership, destination, time, mode and route. Mobility tools are defined in Scott & Axhausen (2006) as any equipment that enables travelling, from Public Transit (PT) pass to driver's license and car, and more investigated in Chapter 3,
- The *decision architecture* details the ordering and the articulation among the mobility choices and the overall model type, whether it is a four step, an activity-based, a tour-based or another model. It also includes information about demand pivot procedure implementation studied in Daly et al. (2012),

- The *traveller segmentation* details the number of population segments and the socio-economic criteria differentiating these groups,
- The *activity segmentation* details the number of activity segments and the motives differentiating these groups,
- The *budget constraints* detail the consideration of financial constraints when mobility choices are made,
- The *interpersonal relations constraints* detail the consideration of relationship and interaction effects among household members when mobility choices are made such as the constrained mode choice when a household member is already driving the only car owned by the household,
- The *freight demand* details the treatment of freight, whether it is omitted, exogenous or endogenous,
- The *mobility tool ownership* details the treatment of mobility tool choices, whether it is omitted, exogenous or endogenous and which mobility tools are considered,
- The *intermodality* details the treatment of intermodal trips involving a combination of different modes within the same trip, and which combinations are considered.

2.2.4 Supply representation

The supply representation block illustrates the representation of modes and mobility services and how the supply of infrastructure and services is represented. It is divided among 5 criteria:

- The *modal coverage* details which mode choice alternatives are considered,
- The road *network representation* details the road network specificities, whether it includes nodes and links, for which mode it is used, if parking difficulties and fares or if congestion are considered,
- The *Public Transit network representation* details the PT network specificities, whether it includes network, line or mission, and if PT vehicles frequencies, price, comfort or congestion are considered,
- The *active modes representation* details whether active modes are omitted or considered without or with specific supply network,
- The *other mobility services representation* details whether mobility services other than PT are omitted or considered without or with specific supply network.

2.2.5 Uses representation

The uses representation block shows how the interaction between the demand and the supply is converted into traffic generation for the different modes. It is divided among 3 criteria:

- The *car traffic* details the process to dispatch travellers on the car network with exogenous, endogenous, static or dynamic time values for the links,
- The *PT traffic* details the process to dispatch travellers on the PT network with exogenous, endogenous, static or dynamic time values for the links,
- The *other modes traffic* details whether other traffics are considered and how they are processed.

2.3 The Paris Planning Models

It is necessary to first describe the models studied and their socio-technical background before comparing them. Previous research has already assessed the different Paris region TDMs, but the reports of IAURIF by Nguyen-Luong in 1998 and of the EXPEDITE 2002 European project only focused on giving development advice without illustrating model comparisons. More recently Garcia Castello (2010) has characterized Paris region TDMs along four general classes, but without aiming to compare them. The existing documentation assesses the models independently, but it does not try to confront them against the mobility aspects they are able to reveal. Common denominators for each studied TDMs are the use of a shared Paris region passenger mobility survey – the EGT – last conducted in 2010 and the goal to evaluate multimodal scenarios affecting the demand and the transport supply. The following model descriptions are based on unpublished technical documentation provided by DRIEA, RATP, SNCF Transilien and Ile-de-France Mobilités, and describe the early 2017 model developments.

2.3.1 MODUS

MODUS is an aggregated four step model developed by the DRIEA IF, a French State agency of the Paris region in charge of implementing French State transport policies. It was first developed in the 1990s and the last version was launched in 2009. MODUS has been designed to help decision-making and to feed other local administrations, transport operators and air pollution controller's models. It especially focuses on car flows forecast for a better motorway network representation as DRIEA is a highway operating and managing entity. It is also used for State expertise on road infrastructure projects and large PT projects.

The model structure follows the four step model scheme. The generation step relies on a linear model, the distribution on a gravity model, the mode choice on a MNL and the assignment step is divided between a PT assignment step and a road network assignment step feeding back on the distribution and mode choice step creating a loop. Freight and external trips are exogenously implemented as additional fixed demand matrices.

MODUS divides the Paris region in 1289 TAZ and 50 additional specific zones dedicated to external flows for airports, interurban train stations and zones at the border of the road network. This zoning describes more accurately the denser urban areas. Two temporal scales are considered: the AM peak hour and the PM peak hour. The car peak hours are extended to account for a 2.3h AM peak period and for a 2h PM peak period. These peak flows are calculated from the daily demand matrix generated by the demand model and then proportionally dispatched over the periods to the ratio observed in the EGT before adding exogenous flows.

Three modes are described at the trip level: car, PT and active modes. The road network was drawn by the DRIEA in 2010. It distinguishes 10 road types on 27,000 links and it is used for the other Paris models. It uses flow-speed relationship diagrams for the different road types that are then adjusted with the last observed data. The PT network is drawn from the Paris region operators' network data. MODUS represents mobility by dividing it into 12 different segments for each mode: 2 user segments differentiating PT dependency; and 6 activity segments differentiating home to work/study trips, work/study to home trips, shop trips, leisure trips, non-work based to home trips and non-home based to work trips. At the end of the demand module, car trips are adjusted reproducing the average occupancy ratio observed with the EGT for the AM or PM peak period.

The assignment is performed on VISUM's Tribut module, with a feedback on the demand allowing to take into account congestion effects. The PT assignment is similar but without loop taking into account PT congestion.

2.3.2 GLOBAL

GLOBAL is an aggregated four step model internally developed by RATP, a French PT operator and infrastructure owner which is the historical operator of the Paris metro system. It was first developed in the 1970s and the last version has been released in 2014. It focuses on PT planning and aims to ensure the qualitative and quantitative supply contracted and to size PT infrastructure investments.

The model structure follows the four step scheme. The generation step relies on linear models for the segments: work related trips, education related trips and other activity related trips. The distribution is made out of the processing of external data while the other activity related trips' distribution involves a gravity model. External trips are added after the distribution step with a log-log model for the emissions and attractions linked to train stations distribution and a zonal pro-rata distribution of emissions and attractions linked to airports.

In GLOBAL, the Paris region is divided among 2294 TAZ that can be adapted to each case study. This zoning respects the administrative borders and is established so that one zone encompasses only one heavy rail stop at most. The centroids have been manually positioned to account for each zone's specific environment. The temporal framework is based on a 2h AM peak period reduced afterwards to 1h to encompass the AM peak hours, which vary with the location in the region. The AM peak hour is used for sizing the mobility supply.

The PT network is made of 36,000 links on 1,600 lines operated by 2,000 missions with details about the Level Of Service (LOS), the frequency, and the platform to platform transfer times. The road network is the one set up by the DRIEA. The mode choice at the trip level is modelled using a 2 stages NL model structured with a principal mode choice segmented between long and short trips, and then a second choice level for the minor access and egress mode to PT between active mode and car. The multiple possible paths are considered with a logsum term as described in de Jong et al. 2007.

The road network assignment is performed with a shortest path algorithm taking congestion into account as an exogenous phenomenon and without capacity constraints. The PT assignment is based on a more complex multipath algorithm to account for different perceptions of the generalized cost of a route, unreliable travel times and varying access and egress real length. The PT assignment algorithm assigns stochastic perturbation factors on the network and calculates the shortest path out of 16 different configurations.

2.3.3 IMPACT

IMPACT is a disaggregated activity-based model developed by Significance and Aecom for RATP. It was first implemented in the 1980s as a model complementary with GLOBAL and the current operating version of IMPACT has been released in 2015. Its main objective is to model transport policies' socio-economic impacts on the Paris region with a more detailed user-oriented demand representation fostering fare impacts quantifications.

It is organized around two main modules: a demand module and a supply module feeding back the demand module until convergence. A PT pass ownership modelling step is embedded in the demand module while external trips are not endogenously modelled, but their observed share out of every trip from the EGT 2010 is reproduced.

IMPACT is based on the same zonal representation and supply networks as GLOBAL. The day is divided into 5 periods covering the whole day and distinguishing the AM and PM peak periods. A specific Level of Service (LOS) peak matrix is used for the AM peak period and its reverse is used for the PM peak period while a LOS off-peak matrix is assigned to the other time of day periods.

The mobility demand module is divided into 4 sub-modules dealing with 16 activities modelled at the trip level. A first sub-module for mandatory trips based on 5 trips purposes related to work, education – segmented among 3 education levels – or business affairs has input data about home and work/education locations and runs a 2 stages NL mode choice model. A second sub-module for non-mandatory trips based on 8 trips purposes related to shopping – daily, weekly or exceptional –, leisure – conviviality, walk, other – and personal business – nearby or specialist – uses input data to run a 2 stages NL mode-destination choice, including a strata sampling procedure to reduce the destination choice set to 5 zones. After this mode-destination choice, a generation model sub-module forecasts changes in trip frequencies from changes in travel costs or in trip destinations for non-mandatory trips. Finally, a fourth sub-module models the 3 other supplementary trip purposes. Overall 9 modes are modelled: walk, bike, car driver, car passenger, two-wheeled vehicle, bus, rail, bus and rail, PT and car.

Then the supply module is divided among five sub-modules on a simplified highway network – 51 zones and 153 links – as IMPACT focuses on systemic impacts and not local impacts. A highway congestion sub-module models highway travel costs adjustments, aggregate speeds and congestion measure for the road network; a bus speed sub-module models bus travel costs adjustments; a parking sub-module adjusts highway travel and parking costs; a PT overcrowding sub-module models PT cost adjustments; and a final adjustment sub-module gathers and applies the costs adjustments from the previous supply sub-modules. The total demand is finally compared with the total available supply as a convergence criterion.

2.3.4 ARES

ARES is a disaggregated tour-based model with a structure very similar to four step models developed by PTV for SNCF Transilien, the French public commuter train operator in the Paris region. It is developed since 2012 and has been operating since 2014. Its main objective is to analyse urban mobility with a focus on PT – and especially commuter trains – planning and uses.

The model is divided into a supply module, a principal demand module, a freight demand module, an external trips demand module, a road network assignment module and a PT assignment module. The freight demand module is very detailed as it deals with an endogenous freight demand matrix generated by a specific tour-based model, while the external trips demand module adds a fixed demand matrix. Car ownership is exogenously considered in the principal demand segmentation following the organization of four step models with a linear model for the generation and a gravity model for the distribution.

ARES relies on 1478 TAZ with 76 additional zones for external transits and exchanges, for train stations and airports, and for zones at the border of the road network. The modelled time periods are the AM peak period, the PM peak period and the day.

The mobility supply is made of the base road and PT networks. The latter is detailed with existing vehicle routes and time-schedules. Parking penalties are incorporated in travel costs to account for difficulties and added costs to park a vehicle. 5 modes are considered: walk, bike, PT, car driver and car passenger. Intermodal trips are represented as trips with a principal mode and an access/egress minor mode. The consistency of tours is considered by removing some modes from the choice set depending on the first trip made. The population is segmented among 11 groups based on residence location, car ownership and main activity before a mode choice step made with MNL models.

The road network assignment is performed with a car matrix and a truck matrix simultaneously assigned. A pre-assignment is made with 2010 DRIEA flow data, and then the model processes with its own assignment procedure involving a Wardrop equilibrium. The comparison between the observed and calculated flows allows to get a control procedure to adjust the road network characteristics so that the calculated flows match the observed flows with a fixed error tolerance. The PT assignment is based on a Kirchhoff model to account for non-optimal preferences of generalized time with a maximum number of transfers set to 3. The assignment has a feedback on the demand modules to equilibrate supply and demand and to model congestion.

2.3.5 ANTONIN

ANTONIN is a disaggregated tour-based model described in Debrincat and Merret-Conti (2016) and developed on Cube by Significance for Ile-de-France Mobilités, the mobility planning authority of the Paris region. The first version of ANTONIN was developed in 2000 and the last version has been released in 2015. Its main objective is to give reliable evaluation of policy, major event and infrastructure projects impacts on the Paris region mobility. It especially focuses on a complete urban mode representation to get a full description of urban mobility.

ANTONIN is built around 5 main modules: a LOS module generating the travel times and costs, a demand module generating activity tours to define the OD matrix at the day level, a time of day module to set the analysis period, a pivot module and an assignment module. The fixed external trip matrix is added after the pivot procedure. Mobility tool set ownership successively featuring driving license, car, two-wheeled vehicle and PT pass ownership is endogenously generated in the demand module.

1805 TAZ represent the Paris region respecting administrative borders, natural frontiers, infrastructures and the zone convexity. Each zone has a function unicity linked to the land-use. The zones can be modified to match the study of local projects. Three main periods can be modelled: the AM peak period, the off-peak period and the day. ANTONIN calculates daily OD matrix that are then transformed through factors reproducing the observed shares in the EGT 2010 for the corresponding period of analysis.

The road network has parking constraints details and the PT network has timetables converted into frequencies at the different period of analyses. PT level of service is calculated with a composite cost to represent the different itinerary opportunities associated with the PT mode. Cost calculation is different for users under and over 55 to account for the influence of age over route choice. 7 modes are represented: walk, bike, PT with walk access, PT with car access, two-wheeled vehicle, car driver and car passenger. Intermodality appears for accessing PT. In the demand module, mobility tools ownership is first modelled with MNL models. Second, home-based trips are generated for 8 activities with a stop-repeat model to determine their number. Then a mode and destination is allocated to each primary tour with a 2 stages NL or 3 stages NL depending on the activities. Finally, secondary tours are generated for 6 activities with the same process. A pivot procedure concludes the demand module to reduce forecast errors from calibration data.

In ANTONIN, the assignment step is still under development. The road network currently uses a Cube module with a shortest path algorithm under capacity constraints. The multipath PT assignment incorporates comfort effects based on a specific Revealed and Stated Preferences survey conducted in the Paris region.

2.4 Comparative Analysis Results

The application of the analytical grid yields the comparison table detailed in Table 2.2 and Table 2.3. This table efficiently illustrates how mobility is represented in each model. It also puts forward that main model's features fit their operational entities history and operational needs: MODUS has a finer description of the car mode as its assignment feedbacks, which is logical as DRIEA provides expertise on large infrastructure projects; GLOBAL focuses on the peak hour representation used for sizing PT infrastructures and a developed PT assignment procedure illustrating its main use for studying PT infrastructure projects at RATP; IMPACT is activity based and has an extended procedure to accurately evaluate the demand by motives and with some mobility tools modelling showing its objective to forecast regional impacts affecting user demand; ARES especially focuses on the freight demand and its general tour-based and disaggregated approach matches the commuter train operator aim of SNCF Transilien; ANTONIN also has a tour-based and disaggregated approach with a finer demand representation describing diverse modes and mobility tools ownership as Ile-de-France Mobilités is a planning entity for urban mobility.

Three principal model groups can be drawn from this comparison: the four step model group – MODUS and GLOBAL –, the activity model group – IMPACT – and the tour based model group – ARES and ANTONIN –. These models are articulated around the historical car and PT modes that they represent with a lot of details, and account for many phenomena such as congestion, comfort, parking fares and difficulties and transfer costs between stations or modes. The transport motives are addressed by each model through detailed activity segmentation with at least 6 travel motives dealt with. The temporal representation also yields a lot of results on the peak periods, which are the more stressful for the transport system. The Paris region zoning is also very detailed and reaches the limits of the available socio-economic data collected at administrative unit zone.

The model confrontation also highlights developments potentials for improving the models' ability to provide a full mobility description such as:

- Residential location choice as is done with LUTI models and budget constraints. Even though LUTIs are difficult to implement, an efficient calibration of such model could be valuable as Saujot et al. 2016 states;
- Mobility tools ownership choice that has begun with ANTONIN and IMPACT. It would give information on car fleets trajectories and on PT fare revenues evolution, and could also include interpersonal constraints affecting the availability of each mobility tool in a household;
- Departure time choice as emerging behaviours seems to indicate a shift of the peak hours with a possible future decrease due to teleworking growth;
- New mobility services and intermodality representation that are fostering and quickly growing in the Paris region. Scooter, bike, motorcycle and car sharing seem to be high potential mobility services to incorporate soon;
- Dynamic modelling to account for temporal changes and to represent the non-optimal situations faced in real-life with intermediary phases where equilibrium is not met. It could also benefit from the availability of real-time traffic data, which is now available from many PT operators.

BLOCKS AND CRITERIA			MODUS	GLOBAL	IMPACT	ARES	ANTONIN
Spatio-temporal representation	Analysis unit		Trip	Trip	Trip	Tour	Tour
	Zone	Zone # *Avg surface* *Avg pop.*	1289 *9.8 km²* *9.3k*	2294 *5.2 km²* *5.2k*	2294 *5.2 km²* *5.2k*	1478 *8.1 km²* *8.1k*	1805 *6.6 km²* *6.6k*
	External Demand modeling		Exogenous fixed matrix	Exogenous fixed matrix	Reproduction of the observed inner trips share	Exogenous fixed matrix	Exogenous fixed matrix
	Time Period modeling		AM peak period PM peak period Off-peak hour Day	AM peak period reduced to 1h	AM peak period PM peak period 3 Off-peak periods	AM peak period PM peak period Day	AM peak period Day
	Departure Time (DT) modeling *Modification of DT*		Reproduction of the daily share *Omitted*	One time period modeled *Omitted*	Reproduction of the daily share *Omitted*	Reproduction of the daily share *Omitted*	Reproduction of the daily share *Elastic for Car*
Demand representation	Mobility Choices	Location Travel Ownership Destination Mode Time Route	Omitted Considered Omitted Considered Considered Omitted Considered	Omitted Considered Omitted Considered Considered Omitted Considered	Omitted Considered Considered Considered Considered Omitted Considered	Omitted Considered Omitted Considered Considered Considered Considered	Omitted Considered Considered Considered Considered Omitted Considered
	Decision Architecture Aggregation level *Feedback and pivot procedure* *Mode choice structure*		**4 step** **aggregated** *Car assignment feedback on Distribution* *Mode choice*	**4 step** **aggregated** *No feedback* *Mode choice*	**Activity based** **disaggregated** *Assignment feedback on Demand* *Mode and Mode x Destination choice*	**Tour based** **disaggregated** *Assignment feedback on Demand* *Mode choice*	**Tour based** **disaggregated** *Assignment feedback on Demand* *Pivot procedure* *Mode x Destination choice*
	Traveler Segmentation *Segmentation criteria*		2 groups *PT dependency*	Omitted	Omitted	16 groups *working, studies, vehicle, location*	2 groups *income*
	Activity Segmentation *Segmentation criteria*		6 motives *work, education, shopping, leisure, home-based*	6 motives *work, education, childcare, other*	16 motives *Mandatory: work, education* *Other: shopping, leisure, other*	8 motives *work, education, shopping, leisure, accompaniment*	13 motives *work, education, shopping, leisure, other*
	Budget Constraints		Omitted	Omitted	Omitted	Omitted	Omitted
	Interpersonal Constraints		Omitted	Omitted	Access to the household car(s)	Omitted	Omitted
	Freight Demand		Exogenous	Omitted	Omitted	Endogenous	Omitted
	Mobility Tool Ownership		Omitted	Flat-rate *Car variable*	Explicit *driving license, car, motorcycle, bike, PT pass modeling*	Omitted	Explicit *driving license, car, motorcycle, PT pass modeling*
	Intermodality		walk x PT within PT	walk/car x PT within PT	walk x PT bus x rail car x PT	walk x PT within PT	walk/car x PT within PT

Table 2.2 – Analytical framework comparison of Paris mobility models (1/2)

BLOCKS AND CRITERIA		MODUS	GLOBAL	IMPACT	ARES	ANTONIN
Supply representation	Modal Coverage	active mode, PT, car	walk, PT, car	walk, bike, bus, rail, PT, motorcycle, car driver, car passenger	walk, bike, PT, car driver, car passenger	walk, bike, PT, motorcycle, car driver, car passenger
	Road Network representation	car links, no nodes congestion	car links, no nodes parking fare and difficulty	car and motorcycle links, no nodes congestion, parking fare	car link, no nodes congestion, bike, parking difficulty	car and motorcycle link, no nodes congestion, parking fare and difficulty
	Public Transit Network representation	line frequency, fare, transfer cost	line frequency, fare, transfer cost	line congestion, frequency, fare, comfort	line congestion, frequency, fare, transfer cost	line congestion, frequency, fare, comfort, transfer cost, age (± 55)
	Active Modes representation	Omitted	Omitted	Omitted	Omitted	Omitted
	Other Mobility Services representation	None	None	None	None	None
Uses representation	Car Traffic	Endogenous static times Wardrop equilibrium Assignment procedure outside the model	Exogenous static times Shortest Path	Endogenous static times Simplified assignment on 51 zones Car-Bus interaction procedure outside the model	Endogenous static times Wardrop equilibrium	Endogenous static times Shortest Path
	PT Traffic	Endogenous static times Kichhoff law Assignment procedure outside the model	Exogenous static time Multipath assignment	Endogenous static times Shortest Path procedure outside the model	Endogenous static times Kirchhoff law	Endogenous static times Multipath assignment
	Other modes Traffic	None	None	None	None	None

Table 2.3 – Analytical framework comparison of Paris mobility models (2/2)

Conclusion

This chapter has described the main theoretical methodological background of this dissertation, namely the travel demand modelling field. It has first focused on the description of the most usual model structure from which most of the current models have been developed: the four step model. It has briefly described each step in turn and highlighted the limits of this model. The first section concluded on the need to improve the mobility representation in travel demand models by improving the individual trip decision making, and by endogenizing several other mobility and metropolitan phenomena, with the example of mobility tools holding and land-use.

In order to analyze the expressive power of metropolitan transport models, the second section built an analytical framework reflecting the structure of mobility systems and enabling to compare different types of models. The final grid relies on the representation of logical blocks from the economics theory: spatio-temporal framework, demand, supply and uses. These blocks have been further characterized with 22 criteria not only focusing on technical features but also on the mobility aspects described by each model.

The final analytic table resulting from this analysis enables to quickly assess the way TDMs address mobility in the third section. It enabled to study and compare five TDMs used in the Paris region, namely MODUS, GLOBAL, IMPACT, ARES and ANTONIN. This application has illustrated the TDMs' capacity to reveal the different mobility choices and mechanics included in the models, and put forward main model features are linked to their operational use. The model confrontation in this table also highlights the mobility aspects that are still lacking from all the models and sheds light on development potentials.

The discussion provided in this chapter aimed on avoiding too much focusing on the technical and mathematical aspect of travel demand modelling, but rather on the the way mobility is modelled and which are the main phenomena accounted for. A general observation is the need to expand the models and to complete the mobility picture that they enable to draw and forecast. The remaining of this dissertation gives some answers to possible model evolution by incorporating two new and connected phenomena in the TDMs: mobility tools holding and intermodality.

Chapter 3

Mobility Tools Holding: Concept and Modelling Literature

Introduction

Transport technology diffusion within a population is a topic of major interest for industries. transport equipment has first been studied as consumer goods in order to know how many cars, bikes, carts or horses are sold and what will be the expected future sales so as to manage stocks. But these transport equipments were quickly explored by other actors such as economists and policy makers as they have direct effects on a population accessibility to a range of activities, thus influencing a population's economic potential. Indeed, a decision maker has more travelling alternatives with differentiated attributes if she owns several transport equipments than if she only owns a few. These equipments may enable her to access jobs or grocery, shopping and leisure shops on a much wider range. On the reverse, owning an equipment can also be considered as an economic burden: having invested in an expensive equipment, the decision maker may prefer to use it in order to make it profitable even though this option is not always the immediate best one. So owning a transport equipment is a complex phenomenon mixing at the same time a product to consume and a tool giving access to activities, and it has decisive effects on individual travel behaviour.

The diffusion of transport equipments within a population is also tightly linked with transport networks development. The more there is of a transport equipment in a population, the more the associated transport networks should be developed to enable its use at high levels of service. The more transport equipments there are and the more spatially extended the transport network is, the longer activities can be separated and the more urban spread can grow. This is a simple demand causal reasoning, but the reverse supply one stands too. Along this economic approach, the impact of urban growth and the differentiated access to transport networks given by the ownership of transport equipments clearly make transport equipment ownership a social phenomenon too. The effect of connecting a neighbourhood to the transport network has direct economic effects but also important social inclusion of populations ones. More directly, the diffusion of expensive transport equipments for the richer part of a population creates inequalities of accessibility to activities which can be socially questioned as it limits the freedom of move of the unequipped part of the population compared with the other equipped one. Transport equipment ownership clearly is a socio-economic phenomenon.

In developed countries and especially in France, the diffusion of car as a new trendy technology and then as a major tool enabling formerly isolated population to quickly access cities has been an economic and social revolution in the XXth century. Yet now that cars are very spread, that other modes are available and that sustainable development concerns have risen in the population, the place of car in the transport system is criticized and questioned. Another mobility system evolution currently observed in many developed cities around the world is the emergence of several intermediate transport modes as competitors or complements of the traditional car versus public transport system, associated with new subscription feature instead of traditional vehicle ownership. Like many socio-economic phenomena, transport equipment ownership is subject to industrial and populations behaviours evolution.

The study of the transport equipment holding phenomenon in this dissertation focusing on metropolitan mobility representation answers the need to improve the modelling techniques to better represent mobility phenomena that has been highlighted in the two first chapters. This enables considering the effects of these transport equipments on transport projects, and to evaluate the reciprocal effect of transport projects on transport equipments. A model meeting these expectations is able to forecast car motorization rates and public transit smart card sales or any considered mobility service subscriptions evolution associated with new supply scenarios. These topics have an operational interest for metropolitan mobility authorities, for mobility service providers and for metropolitan mobility vehicles manufacturers.

This chapter aims on setting up the frame for discussing the mobility tools holding socio-economic phenomenon and its representation within the metropolitan mobility system. These models have first been historically used with the spread of cars during the first half of the XXth century. Until the beginning of the XXIst century, their development has been mostly driven by car ownership models. Little by little, other transport modes models are added with the car models as a main reference and motorcycle and public transit subscription models are beginning to appear. But these isolated mobility tools holding models do not display the complexity of the individual choice of building a personal mobility tools portfolio enhancing the joint-holding of several mobility tools phenomenon. The goal is to emphasize which principles have been built and which representation techniques are used in the literature to address the mobility tools holding phenomenon. The identified modelling techniques employed to study this phenomenon belong to the econometrics mobility demand field, mixing aggregate consumption statistical approaches and discrete choice modelling tools.

In order to display the complexity of this phenomenon and the socio-economic logic driving the different models developments, this chapter begins by setting up the vocabulary issues and the conceptual context of mobility tools portfolio holding in the mobility choice set with a first section. It then describes mobility equipment model structures which are heavily inspired by the extensive car ownership models review from de Jong et al. (2002, 2004a), drawing a precise international picture of these models. It focuses on macroeconomic aggregated models before addressing more detailed disaggregated models, following the historical development of car ownership models. Within this model description, aggregated car fleet models are addressed in a second section, before describing more complex disaggregated private vehicle ownership models in a third section. Then it studies the apparition of mobility services subscription models in a fourth section before eventually describing latest mobility tools portfolio models in a fifth section. These sections on the modelling literature discuss the main theoretical assumptions behind the model executions rather than the mathematical formulations. This approach is claimed to give an overview of the ideas and phenomenon representing guiding the model and their evolution rather than the applied tools which are available in the original references.

3.1 Mobility Tools Portfolio Choice: a Contextual and Individual Decision

This first section focuses on the challenges associated with the mobility tools portfolio choice. In order to reach this objective, it is necessary to define mobility tools. After setting up the choice object, the choice maker, the economic demand, its constraints and the choice time frame are discussed. This process enables to show the limits of today's models regarding the complex mobility tools holding structure and to draw a categorization of the mobility tool framed by the choice temporality and the mobility tool type.

3.1.1 Concept of mobility tool and portfolio

The *mobility tool* term has been introduced by Scott & Axhausen (2006) and is equivalent to the *mobility resource* term introduced by Le Vine (2011). They can be defined as any object granting access to a mobility system. In this research the choice of using the mobility tool term has been motivated by the fact that mobility resource tends to refer to consumable energy goods while the tool term better refers to discrete objects.

The most typical ones are the car and all the vehicles – e.g. motorcycles, kick scooters, bicycles, roller skates – while subscriptions to mobility services such as the smart card for public transit or now the smartphone are less straightforward at first. Parking spaces can also be considered as mobility tools because they clearly reduce the cost of owning a car, improving the accessibility to the car mobility. Another category within mobility tools encompasses all of the licenses regulating the access to mobility services such as driving licenses, motorcycles licenses or truck licenses. The most common mobility tool is probably the shoe while there are very few jump springs in use and they both are rarely studied as one is almost perfectly diffused in the population while the other is almost non-existent. With the growth of application-based mobility services, smartphones can even be considered as a mobility tool too. As one can notice, there are many mobility tools and it is necessary to first select which mobility tool to study. An almost immediate category to exclude from transport equipment analysis is the leisure one encompassing the mobility tools used only for leisure activities and not as an access to the mobility system. This is often the case for skis, skates, running shoes, or vintage collector cars for example. Yet this differentiation is not always so easy, as the case of bikes used for transit and as a sport activity illustrates.

When defining the choice object, it is also important to decide the choice unit: whether the goal is to measure if a decision maker owns a mobility tool or how many mobility tools a decision maker owns. This semantic distinction may not appear very important but the models to implement for representing these phenomena are very different. Indeed, holding several times the same mobility tools is more difficult to model as it can heavily increase the number of choice alternatives. This is all the more complex when dealing with different mobility tools type at the same time. This set of mobility tools can be referred to as a portfolio characterized by its individual elements composition features, so it is important to differentiate a mobility tool holding choice from a mobility tools holding choice which can also be called a mobility tools portfolio holding choice.

3.1.2 Defining the adequate choice maker

Now that mobility tools are defined, it is important to define the choice maker. This question is not trivial, it can yield very different results and displays very high levels of complexity. As explained in Madre (1984); Amatousse & Madre (1986) the meaning of an analysis widely changes when considering the case of households, individuals, adults, adults equipped with driving license or self-sufficient young people choice makers for studying private car ownership. The selection of a choice maker unit must rely on the ownership status of the mobility tool: whether it is a completely private and individualized good such as custom made bikes, or a shared private good such as a family car. This status is not always onefold and family cars can be considered as shared during the out-of-work schedules while they might be individualized by a family member for his daily home-work commute. Even though some mobility tools can be individualized, the decision to get them may not be individually made and would trigger interpersonal relationships. For instance, a family may consider an overall mobility budget for the family: if a child wants to get a car or a public transit smart card subscription, this choice will depend on other choices made for equipping other family members. So the choice unit does not exclude the decisions from interpersonal constraints. The case of company mobility tools lent to company workers also raises the choice complexity as they couple private decisions with economic companies ones following market patterns described in Boutueil (2015, 2016). Ramaekers et al. (2010) displays how company car holding affects travel behaviour.

The ownership status does not only influence the choice maker selection, it can also have an impact on the choice object too. The traditional "full" ownership status does not address every mobility tool use, especially with leased cars or other leased equipment growth. The term mobility tool *holding* is preferred over ownership here as it encompasses every equipment accessible on a daily basis, focusing on the user instead of the owner. The type of ownership can also be associated with the main equipment choice yielding choices among owned car vs leased car for example.

3.1.3 A need for transport network accessibility converted into a mobility tools demand

After dealing with the choice object and the choice maker, the decision maker's needs generating the economic demand must be assessed. As transport is not properly a direct good but rather an indirect good giving access to direct goods, there is no need for transport in itself, and no direct need for a mobility tool in itself. So the need for holding a mobility tool comes from the need to reach activity places. This demand to reach activity places can be very strong such as for work and study activities while leisure activities relates to a less constrained demand. This need can be characterized in many different ways. Le Vine et al. (2013) define a Perceived Activity Set(PAS): the set of activities that an individual wishes to perform. Yet this observed need is difficult to forecast because there is no observation of the decision process that individuals have to build this PAS. Another option is to focus instead on the overall accessibility level granted by a mobility tool by associating an accessibility indicator to each mobility tool. But the conception of accessibility indicators is artificial and can be misleading. The study of this need is also very location dependent. More simple approaches considering only mandatory commute trips mode conditions as the main need for workers and students while considering less mandatory activity needs to be self-included within the residential location can probably yield reliable results too. So mandatory and optional needs for activities seem to be generating the economic demand for mobility tools holding, with a probably more important effect of mandatory needs that should appear. Another factor is important to account for: the versatility and reliability of the mobility tools held. Indeed, some mobility tools provide a very good accessibility but without offering fallback solutions in case of unusual weather or bad traffic conditions, or are not reliable themselves such as old and not properly maintained vehicles. This demand for reliability and versatility is difficult to represent but may appear with a better attraction to large mobility tools portfolios holding than to an isolated mobility tools holding.

3.1.4 Limits and constraints to the mobility tool choice

Similarly with many choices, this choice is also subject to constraints and limits. The first and most obvious constraint is the budget one. Without this constraint, it is very likely that every choice maker would choose almost every available mobility tools holding. The budget constraint can be considered as an overall budget constraint, or as a mobility budget constraint. The first one considers mobility tool as any kind of consumption good, its holding varying with the average purchase power of the household, while the second one considers that a choice maker allocates a specific budget dedicated to mobility needs. Both are close because they have similar sensitivity to socio-economic characteristics, but the second approach triggers different behaviours when the cost of a mobility tool is reduced: the savings made would then be used for another mobility option instead of being used for other general consumption goods. It is also important to differentiate the initial capital investment constraint when buying the mobility tool equipment from the maintenance and use budget constraints. Indeed, the cost of owning a car is often not as much perceived by car owners than the initial cost of buying one. Another constraint which has begun to be introduced in the previous paragraph is the workplace constraint. Whether this workplace is unique or accessible by public transit has strong effects on mobility tools holding. This workplace constraint can be considered within a more general work/study constraints type also encompassing work conditions such as the average frequency of business trips and the availability of teleworking. These constraints can be lifted by national and local policies such as scrapping premium, or by companies when they implement shuttle services for their employees or reimburse taxi fees for night workers for instance. Last, there are some logistic constraints about the burden of carrying the mobility tool held. Public transit smart card has a very low associated logistic constraint while a car or a bike can be difficult to carry and to drop without using them. When reasoning on activity loops, using a vehicle for the first trip of a loop often heavily constrains the other trips within the loop while mobility services subscription removes this constraint by enabling more versatile behaviours.

3.1.5 A diverse choice temporality

In order to complete this picture of the choice environment, it is necessary to deal with one last element, the choice time frame. At the opposite of the mode choice which often happens just before travelling, the choice to get a mobility tool can happen on very different time scales. Roorda et al. (2009); Weis et al. (2010); Le Vine (2011) distinguish long-term *strategical* choices from short-term *tactical* choices. They consider that the mobility tools holding choice belongs to the strategical category with influences from the tactical mode choice. This point of view does not completely display the complexity of the mobility tools holding phenomenon which runs on different time scales. Indeed, the decision to buy a car is heavy as it requires a high monetary investment so it is most of the time considered tactical. Yet registering to mobility services or buying a bike is less burdensome and this decision could belong to the medium-term or even to the short-term tactical decisions.

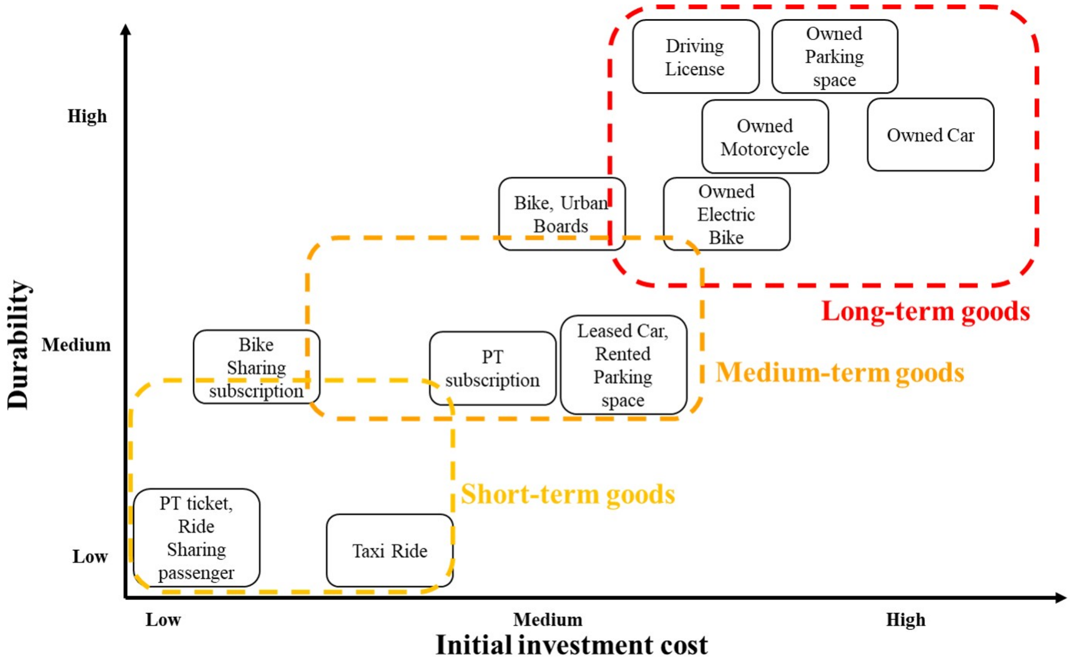


Figure 3.1 – Some mobility tools ranking according to durability and investment cost

This strategical/tactical choice discrimination also relies on the choice object durability: short-lived goods often belong to short-term decisions as opposed to long-lasting goods belonging to long-term decisions. As stated in Cernicchiaro (2013), a ranking of the goods happens because each mobility tool and its use is perceived differently according to its durability and the required monetary investment to get it. The complexity of this goods ranking is illustrated by the fact that different decision makers with different purchasing power will not have the same perception of different mobility tools and the same ranking of alternatives. A segmentation of the users must be made to account for taste variation across the study population. On a more general basis, one-way transport tickets choices can be considered as short-lived immediate decisions – i.e. public transit ticket, taxi or alike trips – while monthly to yearly subscriptions to mobility services choices are medium-term decisions, and vehicles purchase choices are mostly long-term decisions. Some mobility tools are less easily ranked such as bikes, electric bikes, hover-boards or electric unicycles which are goods representing a monetary investment for some individuals and not for others and therefore cannot be considered as usual long-term goods.

Another layer of complexity can be added when considering the ownership status and the development of leasing and shared goods markets. A car which is traditionally a long-term good can now be replaced by a leased car paid on a monthly subscription basis and which can be disposed of anytime, transforming it into a medium-term good. A general ranking of several mobility tools is proposed in Figure 3.1, displaying three non-exclusive goods groups illustrating the complexity of the mobility tool status. This choice time frame also influences the frequency with which the mobility tool holding decision is made as the goods do not have the same durability. The result is that it usually is more easy to move to or switch from a short-term mobility tool than for a long-term mobility tool, and the choice of owning a short-term mobility tool happens more frequently.

3.1.6 Summary

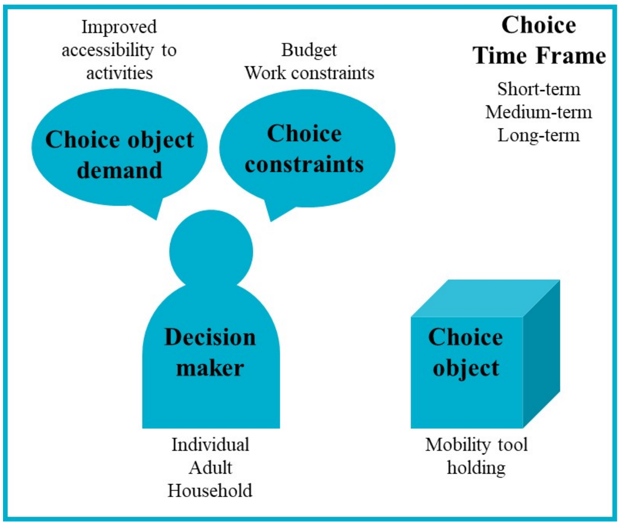


Figure 3.2 – Conceptual frame for the mobility tools holding choice

This first section has enabled to set up the conceptual basis for this analysis of mobility tools holding choice summed up in Figure 3.2. Mobility tools holding choice is a socio-economic phenomenon involving many underlying phenomena and crossing their individual complexity such as the decision maker's individual and interpersonal characteristics, the mobility tool good type, both of these interacting with the social, geographical and economic environment. This enhanced complexity makes modelling mobility tools holding choice difficult and heavily subject to local and individual choice processes. In order to better understand the mechanisms ruling this choice, dedicated statistical analyses are required to assess the phenomenon along this qualitative conceptual description. An observation raised by this approach of the mobility tools holding choice specific characteristics is its inscription within a complex household economic setting, influenced by social conditions. All of these varying along spatial differences and tightly linked with the geographical context.

3.2 Aggregated Car Fleet Modelling

As presented in the introduction, the study of mobility tools holding first begun with a focus on mobility tools fleets diffusion driven by the economics and marketing fields of research. These industrial studies based on emerging XXth century statistical models almost exclusively focused on the car mobility tool and developed a good consumption approach of it. First considering isolated mobility tools without interactions with other mobility tools ownership, some of these representations began to introduce competition among goods patterns in the second half of the XXth century by describing technological innovation diffusion within an existing market, displaying basic substitute goods characteristics. This increment can also be considered as a first step toward including temporal replacement features in the representation of mobility tools ownership, a second one being time series cohort models allocating different behaviours to the several generations – i.e. cohort – coming from the geography research field. In order to display this historical evolution of mobility tool holding modelling and the advantages and disadvantages of each representation, the traditional car consumption model, the more complex multiple substitute goods model, and the dynamic time series cohorts model are described in turn.

3.2.1 Car consumption approaches

One of the first recorded approaches to statistically forecast car holding is exposed in Cramer (1959). In this paper, Cramer models the car ownership diffusion in order to forecast the oil consumption trends. His approach relies on the assumption that each household has a tolerance income level above which the household buys a car. The tolerance level is not known and depends on a specific taste distribution. This taste distribution is assumed to be log-normally linked with the income level of the household. It enables to establish a closed-form expression of the car consumption within a population knowing its income distribution. The advantage of this model is that it easily enables to make motorization forecasts from quite widely available income data. Yet one of the main drawbacks of this model is that it does not account for any other effect than income on car holding.

So every other socio-economic and geographical variable than income are included in the error term and their variation does not impact car ownership diffusion in the model. Other models based on the same income level threshold concept but considering different statistical distributions such as the logistic or the normal distribution have also been developed as detailed in Trognon (1978); Thélot (1981).

An extension of this model has been implemented in Moutardier & Glaude (1978) to account for more parameters: instead of considering a distribution of the income tolerance level, it deals with a distribution of an economic utility tolerance level, the economic utility encompassing several explanatory variables. This simple step enables to account for effects from prices, household head age and other personal characteristics. Accounting for the price effect is a significant improvement because it enables studying a supply and demand equilibrium as opposed to the previous only demand-based models. Another issue with these models is that they only forecast consumption rate in percentage instead of consumption values in quantity. Thus Moutardier and Glaude have also developed variable threshold values to account for quantities forecast: the model now forecasts the share of the saturation threshold of goods to consume, this threshold being determined by an optimization process. The previously described mobility tools holding choice frame can be used to describe these first traditional car consumption models with a car mobility tool studied, decision makers aggregated by income groups, economic demand and choice constraints being confounded within the income variable and only long-term choices considered, without considering the replacement effect.

3.2.2 Consumption of multiple goods

An improvement of these modelling theories dealt with a choice object evolution driven by the marketing research field with almost no application to the transport research field. Instead of focusing on one good consumption, these approaches consider the consumption of several goods at the same time. A first representation introduced by Rault (1969); Ashford & Sowden (1970) is a generalization of the previous one good consumption threshold models by adding another dimension: instead of considering one income level threshold for one good, one threshold level is generated for each of the studied goods.

But no substitutability patterns appear: this new degree of complexity in the consumption relationship is introduced by Trognon (1978) which models a perfect technological substitution relationship between two goods. The example used in the paper is the one of the television market with the diffusion of black-and-white televisions and colour televisions, the colour television being a more expensive improvement of the previous black-and-white television technology. An income threshold is generated for each good, but with a prevalence of the more advanced good: if the income threshold of both goods is reached, then only the more technologically advanced good is consumed by the household. Yet this approach does not account for imperfect substitutability and is due to the underlying consumption concept behind this approach that consumers prefer to consume the more advanced good.

The approach of Lancaster (1966) considers that the economic demand is not for consuming a good in itself, but rather for benefiting from the characteristics a good offer, applying the economic utility concept to the good consumption field. The main advantage of this approach is that it enables to move away from the idea that the consumer demand is for one specific good to the idea that the consumer demand is for several characteristics that a good gives access to. As such, combinations of goods can give different satisfaction levels because they produce different answers to the consumer's demand. Lancaster goes one step further by stating "goods in combination may possess characteristics different from these pertaining to the goods separately" (p.134) which is the base concept of portfolio effects and the one that this dissertation proposes to introduce in travel demand models. This multiple characteristics approach also enables lifting the issue of including direct price effects which were absent of the previous approaches though indirectly considered within the income threshold values. Overall, these approaches have enabled to shift from very restrained choice object, demand and constraints to more flexible concepts with goods being indirect vectors of the real economic demand. The choice demand is now subject to the composition of the goods consumed and to the choice constraints enabled to some extent by diminishing utility values when constraint variables are considered in a model.

3.2.3 Considering a temporal effect with a demographic segmentation

These consumption approaches still lacked of one important variable: time. The time effect considered here is not the choice time frame discussed in the concept section, but the dynamic evolution of car holding. Time is often neglected by applied transport econometric models because it is difficult to find reliable data sets following individuals or household over a long time period to calibrate a model. The models usually take socio-economic variables as inputs and it is the dynamic patterns of these socio-economic variables – built by socio-economic forecasting organisms – that is used to account for temporal effects such as in Dargay & Gately (1999). A consequence of this approach is that car ownership models built in the second part of the $\text{XX}^t h$ century have mostly failed to capture the so-called peak car phenomenon displaying a car ownership threshold reached in several developed countries, because they were unable to capture temporal taste variation and the diminished attractiveness of car ownership for younger populations.

In Madre & Gallez (1993), Madre and Gallez put forward the advantage of using demographic cohort models to capture dynamic behaviour evolution within a population with an application to the French car fleet forecasting. Their model inspired by the demographic field of research distinguishes the life-cycle moments effect measuring the importance of the individual age on the choice, the cohort effect distinguishing individual by their birth year's decade and enabling to access generational behaviours, and the period effect displaying the impact of the socio-economic context on the choice. They represent the diffusion of the average number of vehicles per adult in order to be able to study household structure effects too. Yet the main drawback of this approach is that it is difficult to incorporate an income variable in the model, and that it is mostly indirectly captured by the life-cycle moments effect.

A solution to still account for other socio-economic variables effect is to build an econometric model segmented by sub-models dedicated to each generational cohort such as in Klein & Smart (2017) to study the car ownership behavioural differences displayed by millennials[1]. This approach gives a lot of information but requires the implementation of several models with different efficiencies. Each of these models should have the same explanatory variables to be comparable, which implies not optimizing the sub-models for each cohort.

Aggregated car fleet models may seem outdated now that a new generation of disaggregated models based on large databases enabling more detailed studies of car ownership as a diverse phenomenon sensitive to many social, economic or geographic determinants. Yet, such databases often are so much detailed that they raise privacy issues and are not easily accessible. In most emerging countries, the passenger travel survey required to calibrate the models are not yet implemented

[1]Aside from the technical discussion, it is interesting to notice that the results shows that the main difference displayed by American millennials is that they pursue longer studies than previous generations, delaying their entry on the job market and their access to an economical independence. Thus, they do not have different car ownership behaviours, but the paper suggests that it is mainly this delay for accessing economic independence that is responsible for the observed car ownership threshold, and not the peak car phenomenon.

too and only aggregated statistics are available. In these cases, aggregated models enable to get over the issue of data access and to easily study the general evolution of a mobility tool holding without much data. The communications Trouve et al. (2018, 2020) display the use of standard log-normal statistical models to forecast car ownership for metropolitan areas around the world, and enabled drafting expected growth rates from relatively accessible income statistics and motorization rates. Another application of these models is in integrated simulation models where car fleet forecasting is only a module within a larger transport model. They are typically implemented within logistics models focusing on car sales or more generally the cost of the car mode for society. In the TREMOVE model developed by the KU Leuven and Standard & Poor described in European Commission et al. (1999); European Commission (2007), an aggregated model forecasts the demand for car kilometres based on economic characteristics and transforms it into a vehicle demand by applying average vehicle occupancy rates by vehicle type. A model of car use and replacement is used after this module, representing the yearly surviving stock with the car age and thus displaying the new cars demand by subtracting the car surviving stock from the overall car demand. The OECD (2010) study displays a similar approach within a smaller model.

3.3 Disaggregated Private Vehicle Modelling

The next level of model refinement shifts from aggregated to disaggregated models thanks to discrete choice theories and technological development with improved computation capacity. Most of the current studies use this disaggregated model type when household or individual data is available because they enable to display micro-economic behaviours, even though they are not systematically more accurate than aggregated models. After de Jong et al. (2004a)'s main literature review of car ownership models comparison mostly based on aggregation levels, Anowar et al. (2014a) refines the comparison to better account for the disaggregated models' differences. They focus instead on how car ownership is modelled, whether it is exogenous – without another phenomenon – or whether it is endogenous – jointly with another phenomenon –, and with a static versus dynamic representation differentiation. The exogenous and endogenous categories are a bit misleading as car ownership is an endogenous variable for both. Yet it shows that vehicle ownership is now mostly considered in interaction with other phenomena. The dynamic versus static discrimination is also relevant but the number of dynamic models is still not large. In this section, standard models representing vehicle ownership separately from other phenomena are briefly investigated before presenting joint choice models including vehicle ownership endogenously, then specific latent class models enabling to statistically identify population categories, to finish with dynamic vehicle ownership models. This way of displaying the different features of the models enables to steadily increase the complexity of the mathematical formulation.

3.3.1 Standard discrete choice models use

The standard models are derived from typical discrete choice models from the logit or probit families depending on the error distribution of the utility function considered. Operational car ownership models mostly use these such as the ANTONIN model run by Ile-de-France Mobilités – the Paris region mobility planning authority – in the Paris region and described in Debrincat & Meret-Conti (2016). ANTONIN's car ownership module is a succession of binary logit models first representing the household ownership of one vehicle followed by stop/repeat models to add another vehicle – repeat – or to stop. These successive models enable to get the final number of household vehicles. The driving license holding models first represent driving license holding for the household head, her partner and other adults, the car ownership model then describe whether the household holds a car or not, and then the number of cars owned, including the number of driving license held in the household as an explanatory variable. Last, the motorcycle holding model represents whether the household holds no, one are over two motorcycles, including car holding and driving license holding explanatory variables. All of these models within ANTONIN are built with more than ten socio-economic explanatory variables including household income levels, education level and geographic household location.

The standard model type is also displayed in the research field with the example of Soltani (2017) modelling vehicle ownership in Iran with a nested logit. It deals with the issue of several household vehicles ownership by building a first nest level stating whether the household owns a car or not, and the second level modelling the number of vehicle choice. Several variables about land-use mix entropies are used and illustrate the link between car ownership and geographical variables, suggesting that vehicle ownership models could fit within Land-Use and Transport Integrated(LUTI) models.

Dissanayake & Morikawa (2010) also uses a nested logit model of car and motorcycle ownership but only with dummy variables and alternative specific constant to show the vehicle demand segmentation and ownership decision structures. For each of these models, income is always one of the most significant variables to describe vehicle ownership, but it is most often used as a linear variable and not tested as a model segmentation.

3.3.2 More complex model structures

Other models deal with the vehicle ownership phenomenon jointly with other discrete phenomena such as the mode choice or the housing choice. One of the first paper dealing with this representation is Train (1980) which jointly models car ownership and the home-work trip mode choice. The car ownership choice is made at the household level while the home-work trip is made for each worker, keeping revenue and average car cost variables. Other studies focus not only on the vehicle ownership but also on the vehicle fuel type such as in Brownstone et al. (1999) focusing on the US vehicle market. Salon (2009) even models three choice decisions on residential location, car ownership and commute modes within the same multinomial logit model.

More statistically refined models enable to extend these models mixing several phenomena and including vehicle ownership, to joint mixed discrete-continuous relationships. Eliasson & Mattsson (2000) set up a model representing household location and house type, car ownership level, trip frequencies to all destinations, and mode choice for each trip while considering time and budget constraints. The final formulation is similar to a nested logit formulation even though more complex. Yet the purpose of this study analysis is not to forecast car ownership but only to endogenise it within the trip modelling process.

The theory of discrete-continuous models has mostly been formalized in Bhat (2008) and applied in Bhat (2005); Bhat & Sen (2006). The so-called Multiple Discrete-Continuous Extreme Value (MDCEV) model has first been developed on the discrete choice of activity and the continuous number of hours allocated to each activity within a limited time budget constraint. The 2006 paper is of more interest to this chapter as it is directly applied on discrete vehicle holding and continuous vehicle mileage for each vehicle in the household. This application of this model enables to access the mileage per vehicle type, thus facilitating the study of a household impact on greenhouse gases emissions when considering average emissions per mile depending on the vehicle type, or the impact on the road capacity when considering the vehicle size. The exogenous variables included in the MDCEV model are gathered within the socio-demographic category, the residential location category and vehicle type attributes. As stated earlier, another advantage of this model is that it deals with satiety and budget constraint effects.

The 2008 paper goes a little further on building a nested version of the MDCEV to illustrate the allocation of different time budget per activities, supporting the idea of an unconscious budget allocated to mobility expenses.

3.3.3 A focus on demand segmentation

Instead of representing vehicle holding in addition to another phenomenon, some studies focus instead on how to build a better segmentation of the population to improve the models. Anowar et al. (2014b) displays latent class models to forecast car ownership and compare unordered versus ordered multinomial logits. The idea behind the latent segmentation is to statistically dispatch the observations among a fixed number of segments, and then to apply a model with specific parameters for each population segment[2]. The process developed in this analysis is to begin with two segments, then to add a new segment until the Bayesian Information Criterion of the overall model deteriorates. The four modalities of the choice are the number of household cars ranging from none to three and more cars, and the exogenous variables are socio-economic household characteristics and land-use characteristics including accessibility indicators. It is important to note that the segmentation is exclusively based on the dependent variables included in the model and cannot be done on other characteristics. The explanatory variables appearing in the utility function describe transit accessibility and entropy indicators, household demographics such as the number of household members, the number of PT pass holders, the number of driving license holders, the number of employed adults, children, students and retirees, residential density. A drawback is that the model lacks of data on income.

The results show that the ordered logit does not improve the efficiency of the model and that the number of segments to optimize the model is two. The segments are depicted as transit averse versus transit friendly and display very different coefficients associated to opposite behaviours which were anticipated by Brownstone et al. (1999). Even though the latent segmentation approach is interesting, the results were quite expected and implementing mathematically complex models to reach such conclusion is as bit disappointing as it would probably appear in a preliminary analysis of the data.

[2]It is important to differentiate a proper segmentation from a variable segmentation. The first one implies a different model for each segment, while the second one implies a same model with a variable taking different values depending on the population segment. The segmentation is quite heavy to implement compared with the variable segmentation, but it gives a lot more insight on specific populations behaviours while a variable segmentation is mostly a variable transformation.

3.3.4 Dynamic models

Similarly with the previous section, this one ends with dynamic models descriptions. At the opposite of the previous models addressing the static car holding issue, dynamic models mostly deal with the vehicle replacement rate in order to study car sales and the household car fleet strategy. Generally, these stock replacement models are encouraged as they capture the inertia of the car holding phenomenon, while pure consumption diffusion models display high ownership variations when socio-economic explanatory variables change a lot. The disaggregated dynamic approach was initiated by John Rust with his study on the replacement of bus engines in Rust (1987). This paper describes the maintenance strategy to adopt to optimize bus engines use, which is the adapted to the vehicle holding case. The model is then further refined with Markov decision processes in Rust (1994).

A review of dynamic ownership models is conducted in de Jong & Kitamura (2009). They are all based on the hypothesis that the decision of keeping, replacing, or getting a new vehicle can be considered as a key life event as described in Verhoeven et al. (2005), and happening roughly every year. The principle is that for each time period, a car holding and replacement decision process is set for a household depending on the current car status and associated attributes. For each new time period, the car status deteriorates until the utility of the household for replacing or scrapping the car dominates the utility of keeping the car.

The dynamic car ownership process is also well described and applied in France with Cernicchiaro (2013); Cernicchiaro & de Lapparent (2015). Cernicchiaro's model builds on Rust's one to implement an optimal use and stop problem to answer the car life-cycle maximization problem under annual mileage demand and budget constraints. The time period is set at the year, which is quite common for these dynamic models. Cirillo et al. (2015) also built a similar dynamic model on synthetic populations, accounting for the population heterogeneity. The study in Glerum et al. (2013) even mixed the dynamic approach with discrete and continuous models for representing car ownership depending on the fuel type and usage, but without building on the modelling framework developed by Chandra Bhat.

To sum up the contribution of this section to the chapter, the development of vehicle ownership models is mostly lead by discrete choice theory models, and mainly focuses on three elements. First, improving the statistical representation of the choice process to account for the complexity of modelling strategical and tactical choices. Second, representing interactions with other decisions such as car use or residential location to include car ownership within life decisions process. Third, displaying dynamic features to show the time evolution of this phenomenon. These developments are almost all conducted on the basis that the household is the decision maker, and with a car choice object when referring to the conceptual frame introduced in the first section. An opening of these car models to other vehicle types would also be a good development trajectory as initiated by Nagai et al. (2003); Hsu et al. (2007) with motorcycles and the review of bicycle ownership models in Muñoz et al. (2016). A recent contribution by Bayart et al. (2020) also highlights new studies including driving license holding analysis. Driving license is a specific mobility tools because it can almost be considered as a diploma, with an evolving perception from young adults suggesting an important age cohort variable effect observed in Ortar et al. (2018).

3.4 Mobility Services Subscription Modelling

Aside the vehicle ownership models which are the most studied in the literature, recent studies are beginning to address the phenomenon of mobility services subscription. While private vehicles are traditionally fully owned and are often considered at the household level as their investment cost is high, mobility services are owned by an infrastructure or fleet managing authority and their access is regulated by individual-level subscriptions. The characteristics of these services are very different from owned vehicles: they often are much cheaper for making a small number of trips, their maintenance is not managed by the user, they can be used for one-way trips, especially as they are short-term goods and their subscription is tightly linked to their use. The development of these mobility services highlights a fundamental switch from ownership-based behaviours to use-based behaviours.

Mobility services were initially only public transport buses, heavy or light rails. More recently, many mobility services are developing such as car sharing, bike sharing, ride sharing, and other sharing services, whether they are station-based or free-floating. Subscribing to these services can also involve owning other equipments such as a driving license for car sharing services, or smartphones for every services only accessible through an application platform. The literature on mobility services subscription is still scarce and there currently are probably more mobility services than research papers on this topic. The search of the key words "mobility services" "subscription" or even "transit pass" or "smart card" on google scholar or on the ENPC dedicated literature search engine did not yield many results in early 2018, and most of these were qualitative and not quantitative studies. Shaheen & Cohen (2013) is one of the rare paper to deal with car sharing services at a worldwide scale, but with qualitative assessment of the services, without a modelling approach.

A first difficulty is to properly characterize these services as many have recently appeared and because there is a fierce competition on the shared mobility market with a lot of companies quickly appearing and disappearing, before quantitatively addressing the issue of representing these services in travel demand models. Due to the low number of models on mobility services subscription in the literature, this section proposes a characterization of mobility services subscription types from the supply, demand and uses perspectives before discussing the few existing models. The aim is to ease the analysis of these mobility tools by setting up definitions on which modelling tools can be built.

3.4.1 Mobility services characterization

As previously stated, public transit is the main mobility service. It can be divided into bus, metro, train services but they are all consistent together as mass transit mobility services providing cheaper access to long distances and are most of the time station-based. The emerging mobility services differentiate from public transit by providing individualized solutions with low-capacity vehicles. The car-based services can be divided among car sharing services providing a full access to a vehicle for a limited time period and which include car rental and leasing services, ride sharing services providing empty vehicle seats to travellers on a route chosen by the driver, and for hire and shared for hire vehicles such as taxis where the driver delivers a ride with an origin and destination chosen by the rider. These car-based services can be extended to motorcycles. On the other hand, many lower speed vehicle sharing services are being developed such as bike sharing services, electric scooter services, ... These services could also be differentiated on a station-based versus free-floating basis, changing the access and egress characteristics of the service.

A first characterization is displayed in Table 3.1. The case of services offering parking spaces is quite difficult to describe with this classification, and it can be considered as an attribute of the car mode rather than a mobility service in itself. So a rented parking space would only be considered as an added cost combined with a car location change. This typology illustrates the diversity of the metropoli-

Some Paris mobility services supply characterization

Vehicle	Train	Bus	Car	Motorcycle	Electric Bike	Bike	Scooter
For hire	N/A	On-demand Shuttles	e.g. Taxi, Uber, Bolt, …	Mototaxi	N/A	N/A	N/A
Ride sharing	Public Transport	Public Transport	e.g. BlablaLines, ...	N/A	N/A	N/A	N/A
Short-term Vehicle sharing	N/A	N/A	e.g. Moov'in Paris, Free2Move, Car2go	e.g. CityScoot, COUP	Vélib'	Vélib', Mobike	e.g. Lime, Bolt, Bird, …
Long-term Vehicle sharing	N/A	N/A	Rental	Rental	Rental	Rental	Rental
Station-based	All	All	Taxi, Car sharing, Rental	All	Vélib', Rental	Vélib', Rental	Rental
Free-floating	N/A	N/A	e.g. Taxi, Uber, Bolt, BlablaLines, …	Mototaxi, CityScoot, COUP	N/A	Mobike	e.g. Lime, Bolt, Bird, …

Table 3.1 – Mobility services characterization in Paris: example in April 2019

tan mobility market segment. The number of operating vehicles/stations or the operating vehicle/station density is also a relevant indicator of the supply but it is not often publicly available, especially for emerging services.

3.4.2 Mobility services supply differentiation

The mobility service supply can also include a subscription typology enabling competition among same mobility market services and product differentiation[3]: whether the service is only based on pay-as-you-go fees without fixed fees, whether it is only a fixed fee with unlimited free use, whether it is only a fixed fee with limited free use, or whether it is a mix of a fixed subscription fee with some added pay-as-you-go fees.

Social pricing can be considered as a modality of the main subscription pricing scheme rather than another category. The proposed segmentation is not only theoretical as it can have high impacts on the mobility service uses. Indeed, the fixed fees with unlimited or limited free use set the marginal cost of using the service to zero, highly inducing subscribers to use the service. The way of paying the subscription fee can also have an impact on the psychological perception of the service: a yearly fee subscription would be seen as a medium-term good for the consumers while a full pay-as-you-go, daily or weekly fee subscription would instead be seen as a short-term good. Such a characterization is displayed in Figure 3.4 with Figure 3.3 illustrating a one-way trip cost depending on trip duration for several mobility services in Paris.

[3]Interestingly, among more than ten electric scooter sharing services in Paris in April 2019, all of the prices schemes are exactly the same. This is probably because the market is still not established and some competitors are waiting for the others to run out of business before changing their pricing scheme.

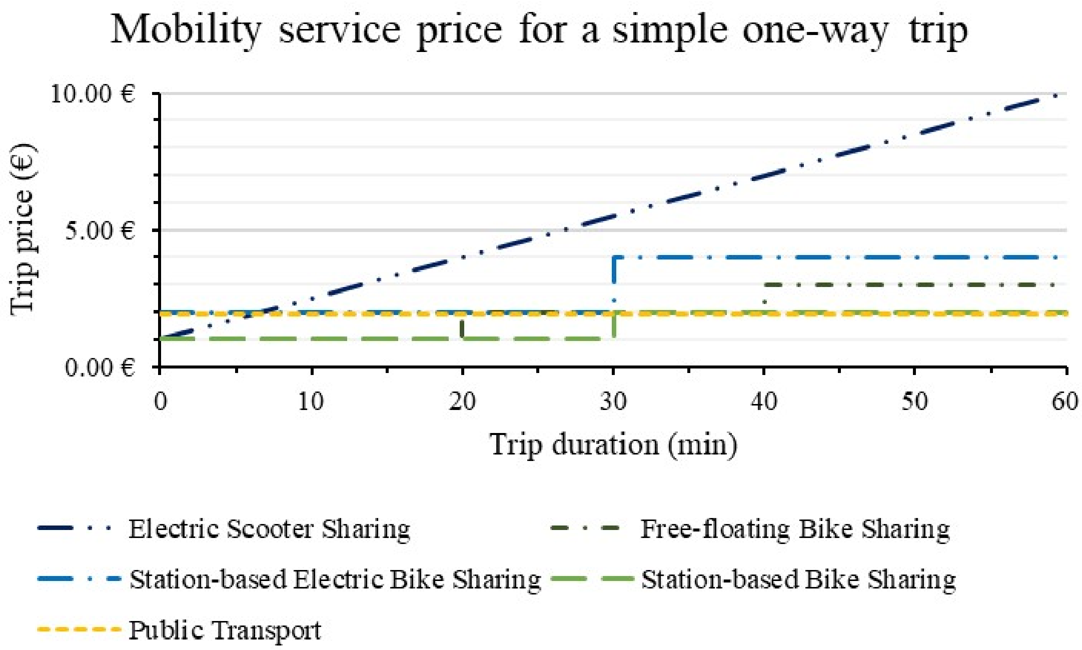


Figure 3.3 – One-way trip price of several Paris mobility services depending on trip duration in April 2019

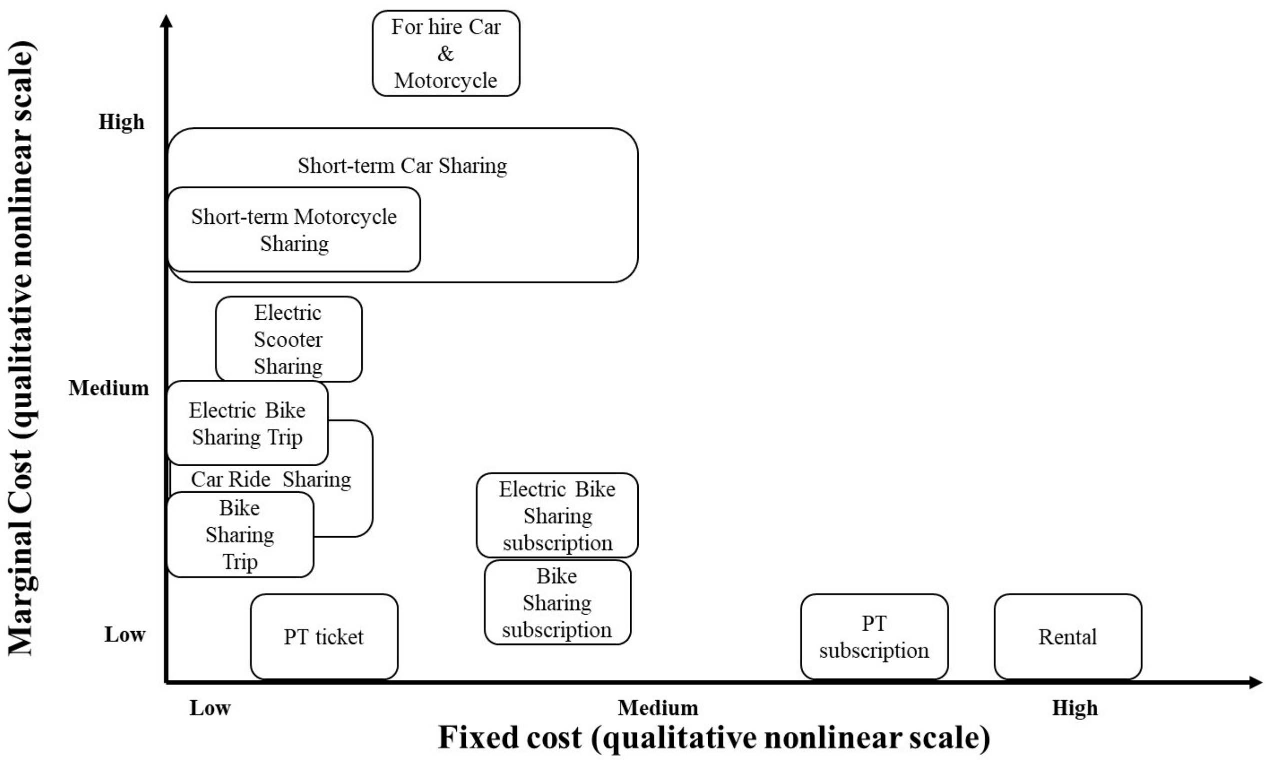


Figure 3.4 – Characterization of mobility services in Parisbased on fixed and marginal costs

Mobility service can also be characterized by how they are accessed. The many applications-based services require a smartphone so they do not reach the whole population. This stands for car sharing services requiring to hold a driving license while ride sharing and for hire services do not have this requirement. The question of driving license holding is not always addressed depending on the field and the difficulty to get a license: in France, driving licenses are difficult to get, with a high cost and a long certification process which must be accounted for. Even though bike sharing or kick scooters are often considered accessible by everyone, there is always a cost for learning the process of the service, and riding a bicycle or a kick scooter in a metropolitan area requires suitable riding skills. The question of the accessibility to the services for mobility disabled populations is also to be considered. The accessibility of the users to the services also raises the question of the parking conditions of the mobility service vehicles, which can be a burden when restrained or at the client's expense.

3.4.3 Market demand segmentation

The demand and uses characterization side is also interesting because each service does not target the same population. The different target populations can be identified by three main factors: the household status identifying the age of household members and the possible interpersonal constraints among them; the activity needs identifying the trip motives and whether they are mandatory or optional; and the economic standard of living identifying the household income per capita and the occupancy status of the household. The activity needs are very important as they can differentiate real alternative service choice from leisure or sightseeing services.

Sometimes the expected demand does not match the real demand and it is important to adjust the mobility service to this information. Indeed, the example of electric vehicles which were first developed for middle to high income populations in metropolitan areas and which were eventually sold in rural areas instead because of an easier installation of charging stations is quite striking. The uses can also be characterized depending on the trip length, duration, frequency, activity, payment method, or perceived marginal cost. The importance of the payment method and the perceived marginal cost are very important as highlighted by Kato et al. (2003); Badoe & Yendeti (2007) showing that a smart card can be a high incentive for using public transit.

3.4.4 Overview of a few mobility services models

After this first characterization step, mobility services modelling must be tackled. While there is some research literature on the quality attributes of public transit such as in Redman et al. (2013), or on the potential uses of smart card data as in Bagchi & White (2005), mobility services subscription modelling is almost non-existent and the quoted papers confirm this lack of literature. The Paris region model ANTONIN deals with smart card data subscription as for any equipment, with a standard binomial logit at the individual scale, happening just after vehicle ownership models thus heavily impacted by the first model results. But not much information on the model formulation was available to better describe it.

In the master thesis McElroy (2009), McElroy proposes a fully dedicated model to address public transit subscription and is one of the more extensive works on this topic. In this model, public transit subscription is jointly modelled with the home-work journey mode choice through a nested structure testing first the mode choice and second the public transit subscription choice then the reverse, without concluding on which is the more appropriate construct. He also suggests that as smart card are short-term goods, their life-cycle is short and they might be better studied with dynamic models.

Last, mobility services subscription characterization and modelling are heavily understudied in the literature, probably because a lot of mobility services are not old and have not yet been large and structured enough and because data on these services is not easily available to researchers. The few documents on the topic suggest to differentiate the mobility services subscription according to the activities associated with them and to link it to mandatory activities mode choice such as work.

3.5 Mobility Tools Portfolio Modelling

The last three sections have displayed separate mobility tools holding modelling approaches, considering holding one of the mobility tools in isolation from others. As this field has initially been initiated for good consumption studies at a time period when there were less mobility tools available, this approach made a lot of sense. Since then, the metropolitan mobility system has evolved and this approach is becoming outdated. Now that several mobility tools are available and that it is a lot easier to make intermodal trips combining several modes within the same trip, a joint mobility tools holding approach is necessary.

This joint approach must be differentiated from the previous strict substitution approach because it enables complementarity patterns. This added degree of complexity also better fits within the complex household decisions structure: because the investment to own a mobility tool is very likely to involve not only the individual but her household too, interpersonal constraints are probably key to representing mobility tools portfolio holding. At the same time, this approach must implement all the special features developed in vehicles and mobility services models, the importance of socio-economic descriptors, and the link with main activities mode choice among others. The aim of mobility tools portfolio holding models is to gather all these pieces together to better frame this mobility decision. Indeed, Astroza et al. (2018) displays the link between mobility related choice structures and population segmentation, favouring such integrated approaches.

This section aims on presenting the evolution of mobility tools portfolio holding models and the current existing models and their main characteristics. It focuses on the first theoretical approaches and the issue of large choice sets, the portfolio models developed and their applications, the representation of accessibility to activities within these models, and recent opening toward time-varying behaviours in turn.

3.5.1 Early approaches and the issue of large choice sets

When considering the first discrete choice models, the main issues raised by portfolio choice models were the Independence of Irrelevant Alternatives(IIA) property and the choice set dimension. Indeed, the multinomial logit models are subject to the IIA property which forbids the existence of correlations among different choice alternatives. It means that if a model is built to forecast car ownership and public transit subscription, the mathematical formulation of the multinomial logit does not allow for additional cross-effects of holding both alternatives together.

A first solution to avoid this issue would be to consider mobility tools portfolio holding alternatives instead of mobility tools holding alternatives. With the previous example, this means considering a choice among (owning a car + holding a public transit subscription), (owning a car + not holding a public transit subscription), (not owning a car + holding a public transit subscription) and (not owning a car + not holding a public transit subscription) instead of (owning a car), (holding a public transit subscription) and (owning none). Even though this representation is very easily implemented with widely spread multinomial logit models, it is still not fully conceptually valid as the IIA property still stands among portfolio choices. The previous example would not allow correlation between the full portfolio alternative and owning a car without holding a public transit subscription alternative while there intuitively is some correlation between these as the first alternative encompasses the second one. So representing portfolio choices with standard multinomial logit models remains a good and theoretically correct option compared with mobility tool choices, but it will not fully display the correlation patterns because of the IIA property. A second solution is to move away from the logit formulation, to other random utility models free of the IIA property.

Another issue quickly rising when modelling the portfolio holding choice is the choice set size. The last example displayed 4 alternatives for 2 mobility tools which is still manageable. But each added mobility tool would highly increase this choice set. More generally for n mobility tools, a full choice set would include 2^n alternatives. Thus dealing with 3 mobility tools already becomes complicated and highly deteriorates the model statistical significance. Since the rise of discrete choice theory and its application to the transport field in the 1970s and in the 1980s, most of the work has been spent on how to improve these models by adding new mathematical formulations and choice structures.

The papers Swait & Ben-Akiva (1986) and Swait & Ben-Akiva (1987) were some of the firsts to propose techniques to reduce the choice set size. Before the mode choice, they include a succession of a deterministic mode choice set model accounting for observed choice set constraints and a probabilistic mode choice set model. This approach is refined with the joint latent choice set modelling within discrete choice models developed in Ben-Akiva & Boccara (1995).

Another operational way of dealing with portfolio choice set size is to reduce the choice set to the most observed portfolios within the representative field data used to calibrate the model. Wiley & Timmermans (2009) is addressing the issue of portfolio holding modelling with multinomial logit models and details how to design choice experiments to analyse correlation among alternatives effects but has not yet been much used for applied models in the mobility tools holding field.

3.5.2 Most recent mobility tools holding portfolios models

The portfolio holding choice models have been first applied in the late 2000s with Scott & Axhausen (2006); Weis et al. (2010); Yamamoto (2009) even though

Yamamoto (2009) does not use the portfolio terminology.

Weis et al. (2010) uses a mixed logit model on a 500 individual respondents stated preferences survey in Switzerland for mobility tools ownership models encompassing car ownership and season tickets ownership. The main goal is to evaluate the trade-offs between season ticket ownership, fuel prices and mileage for revenue managers. The mixed model formulation enables cross-correlations but no interpretation of these appear in the communication and the model is not described enough to be challenged.

Yamamoto (2009) proposes instead to use trivariate probit models for comparing car, motorcycle and bicycle ownership between Osaka and Kuala Lumpur and the effect of the built environment. The multivariate probit models also enable cross-correlation effects. The two cities have high population differences and the motorcycle use is a lot more pronounced in Kuala Lumpur than in Osaka. The data sets used are large and about 176,000 household respondents are registered for Osaka and about 34,500 for Kuala Lumpur. Interestingly, the models show a negative relationship between car and motorcycle ownership for Kuala Lumpur while it is not the case for Osaka. The same relationship appears for bicycle and cars in Osaka and not for Kuala Lumpur suggesting different mobility tools holding structural patterns in these cities which asserts the field importance when studying the mobility tools holding phenomenon. Binomial logit models are also used for comparison and Yamamoto concludes that the latter better represent the phenomenon even though both models are consistent, suggesting that they yield a relevant model approximation even though they are not theoretically adapted.

In addition to introducing the mobility tool term in the literature, Scott & Axhausen (2006) is also a paper that describes some of the first mobility tools portfolio holding models. It is based on data collected through dedicated surveys in Karlsruhe and encompasses about 100 household respondents. A bivariate probit model is used to forecast the number of season tickets and the number of cars per household with a distinction between small and large cars from household and home-work trip characteristics. The results display a substitution pattern between car ownership and season tickets subscription and emphasize the need for portfolio representation.

Habib et al. (2018) introduces a portfolio model with a nested GEV structure for estimating mobility tools holding of post-secondary students in Toronto. Based on a 15,000 individuals survey, the model has a lot of variables encompassing many geographical, socio-economic and household information. The mobility tools encompassed are the driving license, the car, the public transit pass and the bicycle. Results show the importance of the distance between home and university on the held mobility tools portfolio, suggesting that mandatory trips are key for the portfolio choice. The conclusion also explicitly states that larger portfolios are important for understanding intermodal behaviours.

A paper by Becker et al. (2017) focuses on a Swiss national data set with 7,000 individual respondents holding driving licenses to study car-sharing subscription. The different portfolios considered include car, local public transit subscription, national public transit subscription and car-sharing subscription. A multivariate probit is used with a two-levels structure to account for the perfect substitution pattern between national and local public transit subscriptions. The model displays again a negative correlation between car ownership and mobility services including public transit and car-sharing subscription. An originality of this paper is also the use of latent factor attitudinal variables and employment and accessibility indicator variables.

3.5.3 Accounting for accessibility in portfolios models

The accessibility indicator can be considered as a differentiation variable within the mobility tools portfolio holding models. Indeed, some of the studies on this topic consider mobility tools as an answer to an activity set demand. This approach theorized by Le Vine (2011); Le Vine et al. (2013) considers that each mobility tools holding portfolio is built to answer a Perceived Activity Set(PAS). This conception of mobility tools portfolio highlights the importance of each mobility tool's accessibility to the PAS. It leads to the development of several accessibility indicators to include in the model explanatory variables and to adapt the mathematical formulation.

In Le Vine et al. (2013), the utility associated to different mobility tool sets is computed in order to encompass a component describing the accessibility of mobility tools portfolios to the PAS. This portfolio travel utility term is noted $V^{i,travel}_{portfolio}$ and mathematically defined in Equation 3.5.1 where i refers to the individual. This formulation can be interpreted as a logsum representing the utility of the portfolio for fulfilling the PAS, and thus requires an intermediate multinomial logit to compute the $V^{i,travel}_{MobilityTool,journey}$ terms. A $\gamma_{journey}$ coefficient is used to determine the importance of the activity on the portfolio choice. It is generally admitted that constrained activities such as work are more important to fulfil and are associated with a higher coefficient while leisure activities of lower importance have lower coefficient values.

$$V^{i,travel}_{portfolio} = \sum_{journey \in PAS} \gamma_{journey} * ln(\sum_{MobilityTool \in portfolio} e^{V^{i,travel}_{MobilityTool,journey}}) \quad (3.5.1)$$

Astegiano et al. (2017) follows this accessibility to a PAS approach and adds complexity to the choice structure by testing mixed logit for the logsum term and cross-nested logit portfolio choice formulations instead of the multinomial logits used in Le Vine et al. (2013) for the portfolio choice and for the logsum. The paper is based on a 712 individual respondents survey in Ghent, Belgium, and study mobility tools portfolios always encompassing car ownership because they are the most represented in the study population. Four activities are considered to calibrate the accessibility to a PAS: shopping, work, leisure and other. This calibration steps yields interesting parameters results associating travel modes to activities. For this case, the utility of bike appears to be high for leisure and working which is quite surprising and indicates that Ghent is a bicycle-friendly city. Another contribution of this article is to test socio-demographic segmentation variables to display their effects on portfolio choice.

The use of socio-demographic variables is explored more in-depth in Plevka et al. (2018) which implements mixed logit formulations in the portfolio choice to account for a distribution of travel times and cost sensitivity within the study population. A contribution is the simulation of unobserved travel times and costs for unobserved modes using web scrapping techniques to get trip distances by mode before running a regression dependent on this distance by mode and region to get unobserved travel times (calibrated with observed travel times). Plevka et al. (2018) also introduce the effect of the frequency of travel. Unfortunately, there were many convergence issues with this study and the final model is the only one which converged. The study was conducted on 902 household observations from a national German travel survey, with every portfolio choice encompassing car holding. While concluding on the significant effect of PAS and frequency of travel on mobility tools portfolio holding, the discussion calls for more research on analysing population market segments, on the household decision levels and on associating socio-demographic variables in portfolio models.

3.5.4 Dynamic analysis of portfolio holding with models

Another aspect of portfolio holding models is the temporal evolution of behaviours. Indeed, the goal of these models is not only to assess the structure of the mobility tools portfolio holding choice, but also to be used within transport forecast models or for estimating future mobility tools fleets. As such, a logical step would then be to make these models dynamic. A first paper by Dubé (2004) in the marketing research has proposed a formulation of demand for a set of carbonated soft drinks. Even though unrelated to the transport field, the theoretical modelling developed within this paper proposes to model consumption occasions expected by a decision maker, for which a buying decision is made. This succession of decisions is set up to maximize a utility function influenced by the previous decisions and the expected future choice opportunities, and subject to an overall budget constraint. Unfortunately, this model requires longitudinal data on an individual's consumption to be calibrated, data which is usually not captured within household travel surveys but which could be incorporated within future ones.

In the mobility tools portfolio holding research, a few studies have tried to begin to assess temporal evolutions of behaviours such as in Kowald et al. (2017); Becker et al. (2017). Both develop models on two travel surveys to assess time evolutions. An example of results from Kieser et al. (2015); Kowald et al. (2017) between 2000 and 2010 in Switzerland shows that as the life expectancy rises and as the economic and social gap between men and women decreases, the mobility tools portfolios are getting bigger. They also suggest that young generations are less likely to hold a driving license or a car, and that the population density growth and the rise of part-time work favour holding public transit subscriptions.

Except for these first works, a lot has yet to be done to correctly include temporal evolution in portfolio models, one of the big challenges remaining the accessibility to longitudinal data.

Mobility tools portfolio holding models are still young and growing in the transport research literature, yet needed to better understand the role of emerging transport modes and their complementarity with already existing structural modes such as public transport. The increasing number of papers in the late 2010s trying to expand the models from traditional not completely appropriate mathematical formulations to more complex formulations encompassing the effects of several socio-economic phenomena such as accessibility and behavioural change attest this point. That portfolio model type is also beginning to spread to other fields such as tourism or energy consumption in Grigolon et al. (2012); van Cranenburgh et al. (2014); Yang & Timmermans (2017). The current transport applications must be extended to more cases where car holding is less important to study the behaviours of car-less individuals, and focus on household structure effects on mobility tools holding and use choices, which currently are the main challenges to tackle. Improvements on the general and local socio-economic segmentation of the mobility tools holding demand and of the choice structure are also needed to better understand this phenomenon.

Conclusion

This chapter aimed on providing a better understanding of the current mobility tools holding modelling field. It has introduced the phenomenon as a socio-economic phenomenon subject to behaviour changes which is key for understanding future travel behaviour evolution related to emerging intermediate transport modes and new intermodal uses.

The first section has set up a framework highlighting the main issues about the choice time frame which is not so clear with equipments having different durability features; about the mobility tool object which has been defined; about the decision makers which highlights issues when dealing with interrelated households and individual decisions; about the indirect demand for activities conditioned by the mobility tools portfolio and conditioning the mobility tools portfolio at the same time; and eventually about the choice constraints which are not completely observed.

The first aggregated car ownership models resulting from statistical consumption models have then been presented in a second section. Originally mostly based on the income variable, they expanded to socio-economic and geographical variables. Later developments on different substitution patterns and dynamic and cohort patterns have been observed even though substitution models have not often been applied in the transport literature. Another third section details existing disaggregated vehicle ownership models and how their statistical formulations got more complex to account for joint mobility decisions. Latest disaggregated models are focusing on tackling more complex choice structure and on trying to shift from static to dynamic models accounting for temporal evolution.

The fourth section expands the later analysis to mobility services subscription and shows the lack of modelling research on this topic. It proposes different mobility services ranking possibilities and a draft typology is made to better understand the mobility services diversity, and to set up basis for modelling mobility services. A final section describes the recent development of mobility tools portfolio holding models fully considering the substitution and complementarity patterns of several mobility tools. The larger amount of papers issued in the late 2010s than before suggests that it is a promising research field which is beginning to grow out of the former classic travel demand models to portfolio models with a better consideration of activity accessibility variables and dynamic effects.

This overview of mobility tools holding models shows that travel demand models must evolve to endogenously consider the mobility tools holding phenomenon to better account for the traditional structural modes – car and public transport – but also to represent intermediate modes with different holding patterns. Currently, as the traditional modes still are the most represented, these statistical models are better for representing car holding and PT pass subscription than for dealing with emerging services with a low modal share. But they can be specially calibrated with specific development scenarios to assess the potential of new mobility services.

Because most of the previous research has focused on car ownership, mobility tools models directly focus on portfolio modelling even though there is not much information on the mobility services subscription behaviours. In current portfolio models, the place given to the mathematical description of a model is often much larger than the first statistical description of the phenomenon from observations data and the possible decision structure that it can highlight. The segmentation of the study population among homogeneous decision-maker groups seems an important step toward better modelling too.

Most of the existing papers also suggest an intuitive link between mode choice and mobility tools holding choice such as in Habib & Sasic (2014). The structuring role of mandatory trips mode choice on mode choice and the reverse effect of mobility tools portfolio on non-mandatory trips mode choice seems to be a logical start for developing joint mode and mobility tools holding choice models. The research field is beginning to be developed enough and the applications of these mobility tools holding models are operational enough to suggest integrating it into applied mobility models used by transport authorities and companies.

Chapter 4

Statistical Analysis of Mobility Tools Holding in Paris

Introduction

As presented in the previous chapter, mobility tools holding has mostly been considered through separate mobility tools models with an economic consumption approach. Over time, several socio-economic and geographic descriptors have been included to display the link between this socio-technical phenomenon and individual socio-economic characteristics. These descriptors are important because they enable to better understand what enhances or decreases the likelihood of holding a mobility tool. Identifying these potential explanatory variables is necessary before trying to model the study phenomenon and enables to get a first observation of the choice structure.

Chapter 3 has also highlighted the importance of addressing mobility tools holding within portfolio holdings, because holding one mobility tool has effects on whether another is held or not. Instead of just focusing on each separate mobility tool holding descriptors, it is key to study the relationship patterns of co-holdings and more general multiple holdings. When having a higher income generally is a good predictor for good consumption levels, it may not be as much relevant for explaining different consumption patterns among several goods for instance.

After the conceptual definition of the mobility tools holding phenomenon, interrogating what are the household and individual characteristics associated with separate and joint mobility tools holding and what is the structure of the mobility tools holding phenomenon is a logical next step. This chapter aims on answering these research questions by displaying several mobility tools holding patterns and by analysing the effects of socio-economic and geographic descriptors on the mobility tools holding choice structure in the Paris region, paving the way for mobility tools holding modelling in chapter 5.

The way to reach this aim involves the use of several traditional and original statistical analyses of the EGT 2010 data set with R and Microsoft Excel. In addition to marginal descriptive statistics, correlations and mobility tools holding combination relationships analyses are conducted to investigate this topic.

But studying these relationships of consumption among goods rises an issue of choice unit: the consumption of some goods is measured at the household level and of some other goods at the individual level. Three alternatives enable answering this issue: make another survey at the desired level, create mirror variables at the different scales bearing the information from the other scale – when several cars are owned in a household, the average number of cars per person could be considered at the individual scale for instance –, or reduce the population to a study population for which both scales are equal. The latter solution is developed in this chapter.

Considering the availability of different mobility tools information in the EGT 2010 survey, the mobility tools encompassed in this chapter are the driving license, the car, the parking space, the motorcycle, the bike, the Public Transit (PT) subscription and the bike sharing subscription. This choice to include many mobility tools is made to have a wider overview of mobility tools holding than most studies focusing only on the main three or four ones, namely the car, the PT subscription, the driving license and the bike.

The chapter is organized into five sections. The first one describes the data set and the sub-population data features. The second one deals with general descriptors of mobility tools holding in the Paris region while the third section focuses on specific study populations enabling to conduct multiple holdings assessment in the fourth section. The final fifth section switches from a separate sum of mobility tools analyses approach to a more integrated mobility tools holding portfolio analysis.

4.1 EGT 2010 data set characteristics

The EGT 2010 is the Paris region travel survey that was conducted in 2010. It is divided into data sets corresponding to four survey forms: one for the households, one for the individuals, one for the trips and one for the trip legs. This chapter does not account for trips so it focuses mostly on the two first data sets on households and individuals while the study of intermodality in Chapter 6 involves all of them. This first section begins by generally describing the EGT 2010 representativeness characteristics and the Paris region population, before focusing on the way mobility tool holding variables are considered within the survey. The section finishes by describing specific study sub-populations enabling an easier and more complete analysis of the mobility tools holding phenomenon. Official documentation on the EGT 2010 processing are available on the OMNIL website[1].

4.1.1 Paris region demography and representativeness of the EGT 2010

The survey encompasses 35,175 individuals in 14,885 households, representative of 11,415,112 Paris region inhabitants in 4,907,249 households. The detail of the age and gender distribution is presented in Figure 4.1. All of the age group categories have the same 5-year step enabling comparing them, except for the last one which is open ended. This is not an issue because the remaining population over 90 is made of relatively few individuals. The age pyramid shows a high share of young individuals under 5 and of potential active individuals between 26 and 60, with an expected decreasing number for the older populations. A traditional age pyramid generally displays a large population for the lower age group categories, decreasing with the death rates for higher age categories. Here, the age categories between 6 and 25 are under-represented. This probably comes from two effects: first, from education models out of dense city centres; second, from the higher attraction of a world city like Paris for a working population aged between 26 and 60. Paris is also known for the high share of tertiary sector jobs, mostly available for the 26 to 60 age group categories too.

About the ratio of men and women, there are 52.2% women in the Paris region, as opposed to 47.8% men. This ratio is relatively balanced by age group up to 75. Over this threshold, the share of women is much higher, over 60% and even reaching 70% for the oldest age group. This probably comes from the combination of the higher life expectancy for women and the world wars of the XXth century.

[1] `http://www.omnil.fr/spip.php?article81`

Figure 4.1 – Age pyramid and gender distribution in the Paris region

Age group	Women	Men	Total
91 and over	0.18%	0.24%	**0.20%**
86 to 90	0.20%	0.28%	**0.23%**
81 to 85	0.18%	0.29%	**0.22%**
76 to 80	0.19%	0.28%	**0.22%**
71 to 75	0.31%	0.30%	**0.30%**
66 to 70	0.31%	0.32%	**0.31%**
61 to 65	0.32%	0.31%	**0.31%**
56 to 60	0.29%	0.28%	**0.29%**
51 to 55	0.30%	0.28%	**0.29%**
46 to 50	0.31%	0.28%	**0.29%**
41 to 45	0.30%	0.30%	**0.30%**
36 to 40	0.30%	0.28%	**0.29%**
31 to 35	0.31%	0.30%	**0.31%**
26 to 30	0.30%	0.30%	**0.30%**
21 to 25	0.29%	0.29%	**0.29%**
16 to 20	0.32%	0.31%	**0.31%**
11 to 15	0.33%	0.37%	**0.35%**
6 to 10	0.38%	0.38%	**0.38%**
0 to 5	0.38%	0.37%	**0.37%**
Overall	**0.31%**	**0.31%**	**0.31%**

Table 4.1 – Sampling rate of the EGT 2010 by age group and gender

The baby boomer generation can be observed in the age groups between 50 and 65.

When comparing the weighted sample and the unweighted sample the very young age categories are more represented in the sample, and the gender rates do not follow the weighted sample trends between 76 and 90. The sampling rate of the EGT survey is detailed in Table 4.1 to quantify these observations. Overall, the EGT 2010 sampling rate is at 0.31%. This is a bit small but the number of observations remains important enough to conduct valid statistical analysis, especially as this survey was conducted on a stratified random sampling method. The strata are built with geographic and socio-economic variables – i.e. 30 categories differentiated by gender, age group and occupation –. More precisely addressing the table, the red numbers represent the categories where the sampling rate has a 50% positive relative deviation from the average sample rate, while the blue numbers are the opposite. The individuals under 11 clearly are over represented in the EGT 2010 sample while the women over 75 are under represented. The other age groups have similar representativeness with the average sampling rate.

4.1.2 Mobility tools holding within the EGT 2010

Now that base information on the EGT 2010 survey has been presented, understanding how mobility tools holding is measured within the survey helps understand the limits of the possible interpreting of EGT 2010 processing results. When studying mobility tools, the scale on which they are recorded is key for the analysis as explained in the introduction. In the EGT 2010, driving license holding, PT subscription and bike sharing subscription are recorded at the individual scale while car holding, motorcycle holding and bike holding are recorded at the household scale. Socio-economic descriptors at the individual scale are not available for analysing mobility tools at the household scale, while the reverse is possible by assigning household characteristics to every individual in the household. It is also important to consider that parking space is indirectly identified through question items on the available vehicles and their previous parking space location at night. This means that most of the households with a car and a parking space are identified, while households with a parking space and without a car are not identified as owning a parking space in this EGT 2010 processing. It rather is a combined car and parking holding mobility tool called parking space holding in this dissertation.

The exact definition of what is a PT subscription or a mobility tool held and what is the study population considered must also be addressed. Indeed, some mobility services subscriptions can be daily subscriptions which are not proper intermediate goods and rather short term consumption goods which should not be studied separately from a trip mode or route choice. The study population description is also important because it is pointless to study license holding in a population that cannot pass the license test, or to include this population within the general study population, which would yield biased results.

The driving license holding variable considered in this thesis describes every individual owning a full license, not accounting for accompanied driving learning individuals who are not proper driving license holders and who do not have the legal right to drive a car alone. The population considered for driving license holding is the Paris region adults – aged 18 and over – population who can pass the driving license exam in France in 2010.

The car holding variable describes every household having a car available. This encompasses company cars or leased cars which are not owned by the household. Because every household has at least one adult in the EGT 2010 data set, every household can hold a car and the overall household population is considered.

The parking space holding variable records whether a car has been parked on an owned or rented parking space, which excludes free and paid parking spaces. This indicator is biased for cases when a free parking space is available on a regular basis, and used as a held parking space. But these are supposed to happen more often in rural places which does not occur for many households in the Paris region. Even though this variable would better address households holding a car, it is used for every Paris region households in order to avoid dealing with too many different scales, and especially one encompassing characteristics from another mobility tool.

The motorcycle holding and the bicycle holding variables are similar to the car holding variable, but without the level of detail on their ownership status which is not a barrier for this study. The bike holding variable includes electric bike holding, and the whole Paris household population is considered.

The PT subscription variable is the one with the highest number of options in the EGT 2010 so it must be specifically detailed here. Indeed, many subscription kinds are possible at the day, the ticket number, the week, the month or even the year. The EGT variable even describes the PT pass type related to discounts available for some population categories. To simplify this complex scheme of 15 alternatives, the PT subscription variable accounts for any subscription reaching at least a week or 12 working trips, which can incur specific travel behaviours.

The population considered encompasses every individual over 3 because the PT was free in the Paris region for young children under 4 years old.

Last, the bike sharing subscription variable encompasses any subscription on at least a weekly time basis. The associated population is made of individuals over 13 years old as the others were not allowed to register to the Paris region *Vélib'* mobility service in 2010.

4.1.3 Sub-population characteristics

Among the possibilities to solve the mobility tool scales comparability issue, creating new individual variables of household mobility tools such as assigning a household car to some household individuals would introduce errors in the estimation. In order to avoid this issue and to keep the sample free of errors, it has been decided to choose a sub-population for which this issue of scale did not happen: the individuals living in one individual households for which all of the household mobility tools are automatically assigned to the single household individual. This solution also has the advantage that it avoids dealing with the complex household decision structure issue introduced in chapter 3. But this solution is not available for every study because it requires having a large enough sample to be able to reduce it to the sub-population. In the EGT 2010, the subsample is made of 5,036 observations representative of 1,820,690 inhabitants out of the 35,175 observations representative of 11,415,112 inhabitants for the whole EGT 2010 data set. It also limits the generalisation potential of the findings to this sub-population.

Focusing on this sub-population also raises an issue with sample adjusting procedures. While the former data set was representative of the Paris region population, the new subsample would require different adjustments to correctly represent the sub-population. Within this study, the adjustment was kept identical with the one of the whole data set because it was already quite detailed and precisely made on socio-professional, age and gender variables and because the subsample is large enough too as it represents about 15% of the overall sample and 20.8% of the Paris region adults with more than five thousand observations. Further work to improve the adjustment could be made to ensure a stronger validity of the results. Table 4.2 sums up the share of the sub-population in the Paris region population. The older population category clearly is more represented in the sub-population than the younger ones.

Figure 4.2 displays the age pyramid and complementary gender share by age group.

Age group	Women	Men	Total
91 and over	45.3%	44.3%	**45.0%**
86 to 90	61.6%	43.3%	**54.8%**
81 to 85	61.1%	29.8%	**50.6%**
76 to 80	53.1%	28.2%	**43.7%**
71 to 75	41.2%	19.9%	**31.1%**
66 to 70	38.0%	20.9%	**30.6%**
61 to 65	37.0%	21.6%	**29.6%**
56 to 60	29.8%	19.2%	**25.0%**
51 to 55	19.3%	20.3%	**19.8%**
46 to 50	16.2%	18.0%	**17.1%**
41 to 45	11.0%	15.6%	**13.2%**
36 to 40	10.4%	15.8%	**13.2%**
31 to 35	12.7%	20.9%	**16.5%**
26 to 30	14.7%	23.8%	**18.9%**
21 to 25	16.6%	22.3%	**19.2%**
18 to 20	5.0%	3.8%	**4.3%**
Overall	**22.1%**	**19.3%**	**20.8%**

Table 4.2 – Share of the sub-population in the Paris region by age group and gender

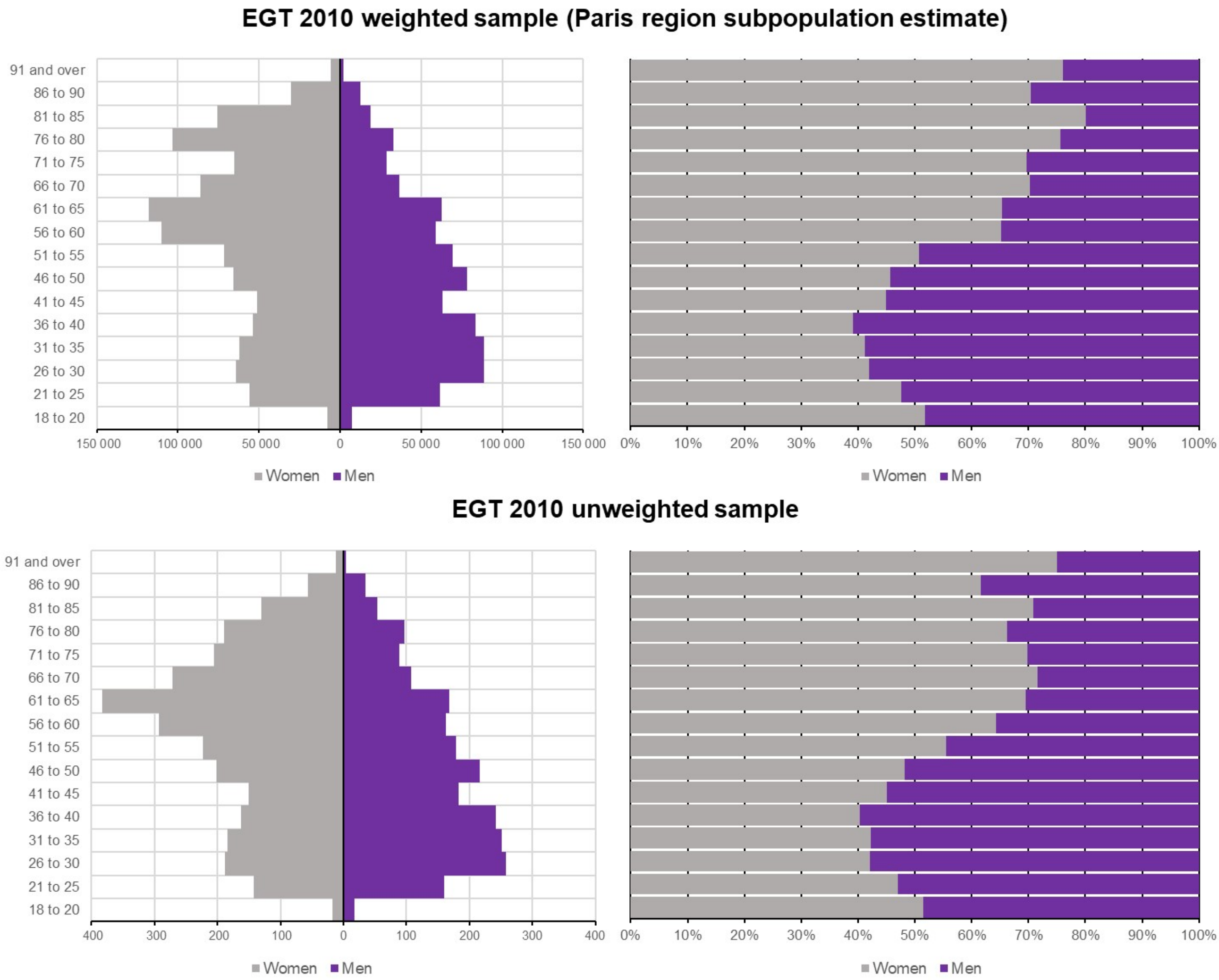


Figure 4.2 – Age pyramid and gender distribution for the sub-population

The sub-population does not show the same distribution of individuals than the whole Paris region population: age groups between 30 and 55 are less represented, which can match with the age when a family is being built and when there are less one individual households. Focusing on the gender distribution, there are more males for the active ages up until 55, and then a lot more women than the Paris region population. Overall, there is a 53.1% share of women versus 46.9% men in the sub-population, which is less balanced than the Paris region population.

Concerning the sampling rates from Table 4.3, their average value is of 0.28%, a little less than for the Paris region. Similarly as before, the oldest age groups are under sampled, but the youngest age groups are not the ones over sampled. Even though there are no proper over sampled age groups, the age groups which are more sampled are the ones between 31 and 75.

Age group	Women	Men	Total
91 and over	0.20%	0.22%	**0.21%**
86 to 90	0.19%	0.27%	**0.21%**
81 to 85	0.17%	0.29%	**0.20%**
76 to 80	0.18%	0.29%	**0.21%**
71 to 75	0.31%	0.31%	**0.31%**
66 to 70	0.32%	0.30%	**0.31%**
61 to 65	0.32%	0.27%	**0.30%**
56 to 60	0.27%	0.28%	**0.27%**
51 to 55	0.31%	0.26%	**0.29%**
46 to 50	0.31%	0.28%	**0.29%**
41 to 45	0.29%	0.29%	**0.29%**
36 to 40	0.30%	0.29%	**0.30%**
31 to 35	0.30%	0.28%	**0.29%**
26 to 30	0.29%	0.29%	**0.29%**
21 to 25	0.25%	0.26%	**0.26%**
18 to 20	0.22%	0.23%	**0.22%**
Overall	**0.27%**	**0.28%**	**0.28%**

Table 4.3 – Sampling rate of the EGT 2010 by age group and gender for the sub-population

When considering the occupation distribution of the individuals in the sub-population in Figure 4.3, a large share of workers and retired individuals appear. It seems that the sub-population can be caricatured as mostly made of single working men and single retired women. It must also be noted that all of the one individual households have adult individuals aged 18 and over, which is practical as they all have access to every mobility tool holding.

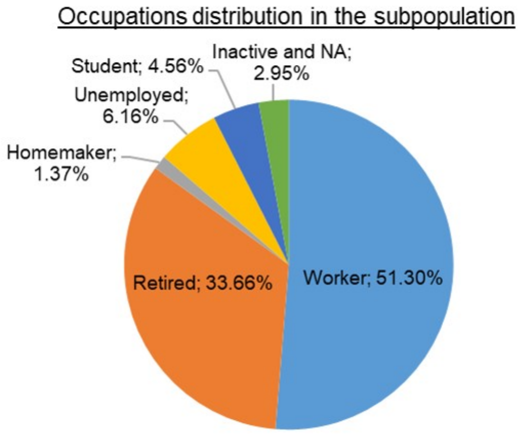


Figure 4.3 – Socio-professional category shares in the sub-population

4.2 Paris region Characteristics

After describing the data set, this section is based on the full EGT 2010 survey for the whole Paris region. Now that the analysis frame is set and defined, it is possible to study correlation effects from some socio-economic descriptors. For the sake of readability, all of the raw numbers are not displayed here but in Appendix B. The figures in the remaining part of this chapter are all illustrations of these statistics aiming to give better visual interpretations of the numbers. While most of the time studies are based on actual holding values, the goal here is to focus on how these evolve with the socio-economic descriptors. In order to better display this effect, the relative deviation from the mean is used, which is an indicator describing the relative distance of the holding values to the mean holding value, weighted by the mean to get percentage values which are less subject to scale issues. The main drawback appearing when studying very low average holdings displaying higher relative deviations from the mean. In order to be able to identify these cases, the average holding rate is given on each figure. Geographical descriptors are first analyzed before addressing demographic, socio-economic, and work-related descriptors.

4.2.1 Geographical descriptors

The first descriptor studied in Figure 4.4 is a geographical descriptor. It is based on the 2008 IAU commune classification into 7 categories: Agglomeration centre communes corresponding to the city of Paris, then other in-agglomeration communes ranked by their density and urbanization level from dense communes to predominantly urbanized communes and finally other communes. Next, out of agglomeration communes are divided between main and other communes before

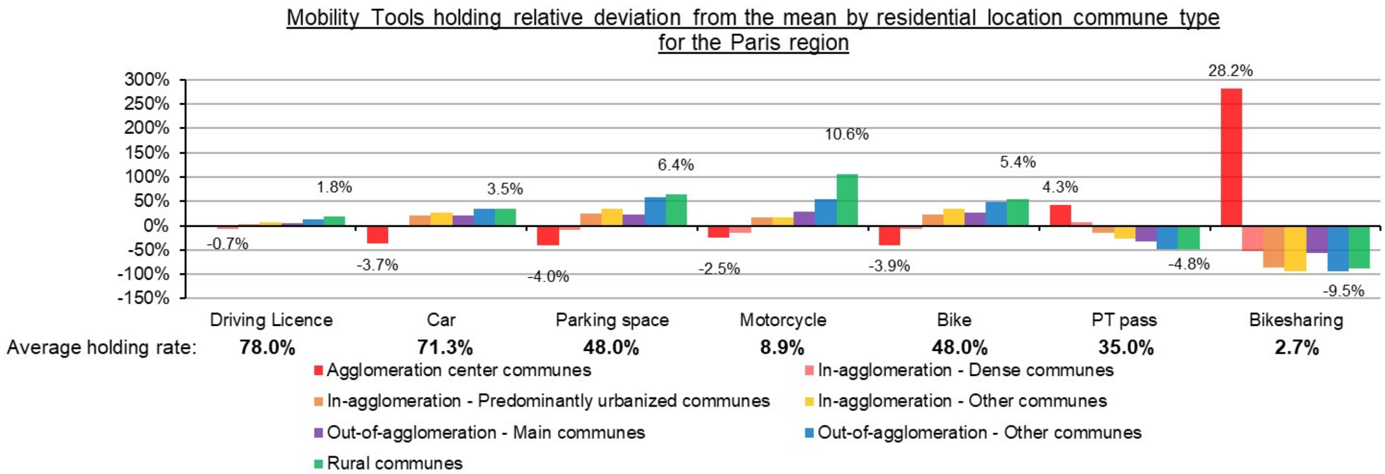


Figure 4.4 – Mobility tools holding by residential location commune type (Paris region)

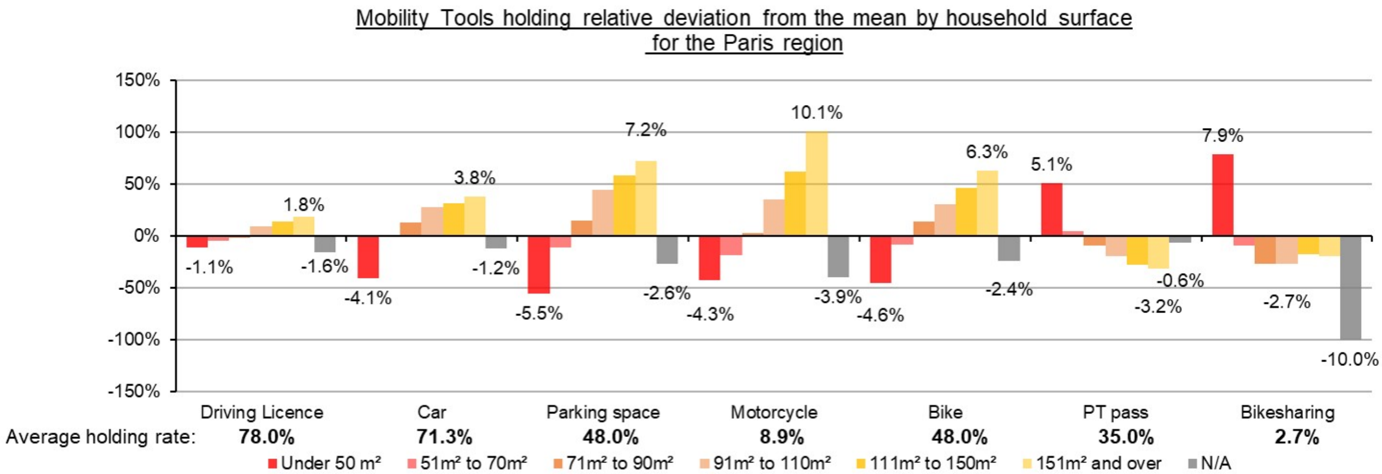


Figure 4.5 – Mobility tools holding by household surface (Paris region)

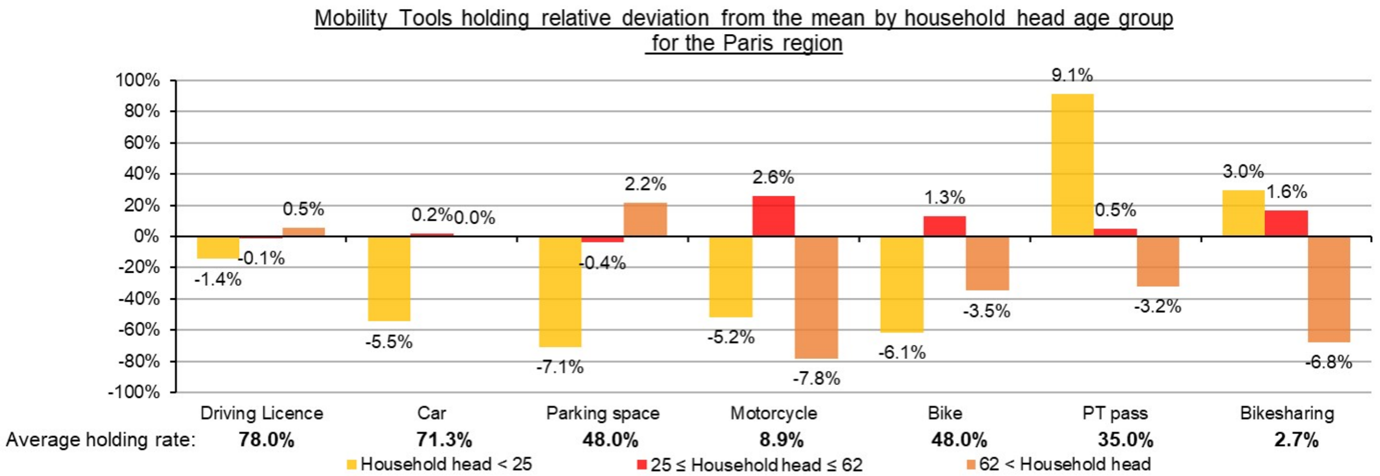


Figure 4.6 – Mobility tools holding by household head age (Paris region)

the last rural commune category. The detailed typology is available on the Paris region open data[2]. The results are pronounced with strong effects of the distance from the agglomeration centre: the less urbanized a commune is, the more driving licenses, cars, parking spaces – which both are heavily correlated –, motorcycles and bikes are owned while the PT subscription follows an opposite trend. The case of the bike sharing system is specific because the service was only available in the agglomeration centre in 2010, which appears in the figure with a very high above the mean value for this commune type. It must be noted that even though driving license holding diminishes with the urbanization level, it is very moderate compared with other mobility tools. It can be explained as driving licenses are a mobility tool that does not incur any maintenance cost, so it is an advantage for anybody to hold one, which is less the case for unused mobility tools with maintenance costs and that must be regularly used for not being an economic burden. The household surface in Figure 4.5 and the housing type data in Appendix B fit these trends when considering that large surface and individual households are associated to less urbanized communes.

4.2.2 Demographic descriptors

After the geographical descriptors, household composition enables to better understand how the household structure is correlated to mobility tools holding. The case of household head age in Figure 4.6 is a little limited because there are only three age groups, but these are built to highlight three principal age groups namely the young and students age group under 25, the active age group from 25 up until 62, and the retired group over 62. These age categories are roughly the average end of study age and access to financial autonomy, and the average retiring age in the Paris region according to INSEE. Driving license holding increases with age which is logical because the probability to get a driving license is cumulative over the age, as it is not withdrawn easily. The car is at the average value except for the young age group lacking of financial autonomy. This also stands for parking spaces but with a higher relative deviation for the retired household heads, which shows that the older the household head age, the higher the chance of holding a parking space while car holding seems to be relatively stable after the 25 years old threshold. Motorcycle and bike holdings show different pattern with an important decrease for the retired household head group, because physical abilities are required for using these mobility tools. At the opposite of the other mobility tools, PT pass holding and bike sharing subscription are dropping with the increasing household head age. These last trends are confirmed when looking at more detailed

[2]https://data.iledefrance.fr/explore/dataset/decoupage-morphologique-dile-de-france/

individual age effects displayed in Figure 4.7. Surprisingly, the relative deviation from the mean of driving license holding diminishes for the oldest age group, the PT pass holding also increases for this group, which has probably something to do with the gender effect because older age groups have a much higher share of women thanks to their higher life expectancy.

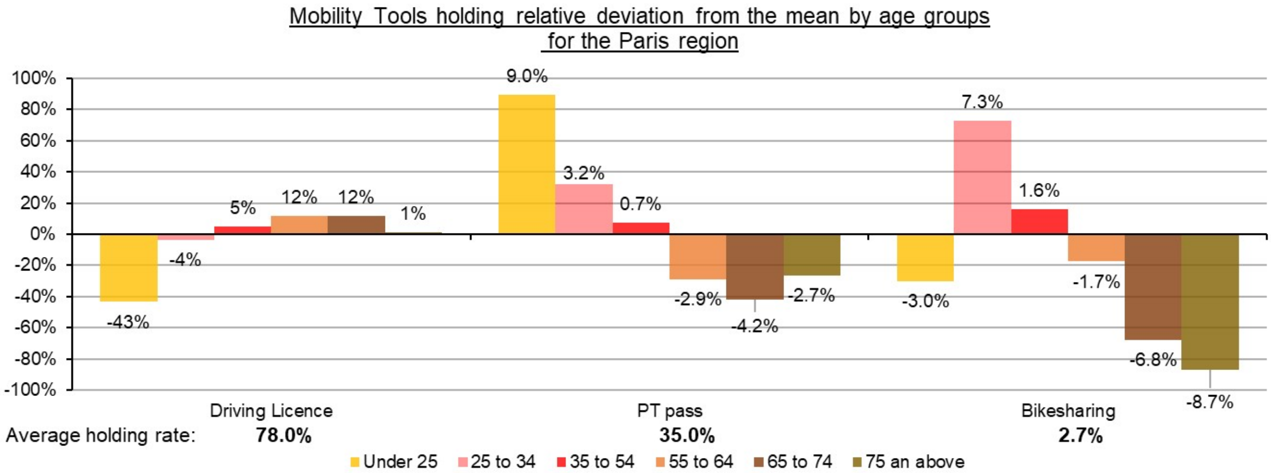


Figure 4.7 – Mobility tools holding by age (Paris region)

Indeed, even though not graphically displayed here, the data on gender shows high mobility tool holding differences. When 84.8% of the adult men hold a driving license, only 72.0% of the adult women hold one, so driving is still a lot gender biased. There also seems to be a little more women over three years old holding PT passes at 36.4% against 33.5% for the men while it is the reverse for bike sharing subscription held by 2.0% of the women over thirteen years old and 3.5% of the men. The overall picture shows that men are more likely to hold a driving license, a bike sharing subscription and a bit less likely to hold a PT pass as opposed to women. This fits the previous observation of different patterns for older individuals because the gender balance falls a lot more on the women side for older age groups, counterbalancing the age effect. Another individual fixed variable has expected effects: the declared mobility disability is generally a negative factor for holding every mobility tool.

4.2.3 Socio-economic descriptors

After these structural variables effects, another well know and much studied variable must be addressed: the household income. Sadly, this variable is not available at the individual scale and does not enable to study individual variations. It also does not account for household size, so it is not very detailed. But the results from Figure 4.8 still show interesting patterns: while the holding rate increases with income levels for every separate mobility tool, it is not the case for the PT subscription which is more favoured by low-income households. Nevertheless, it is not that much rejected by high income households. Interestingly, bike sharing subscription is a lot more favoured by richer households.

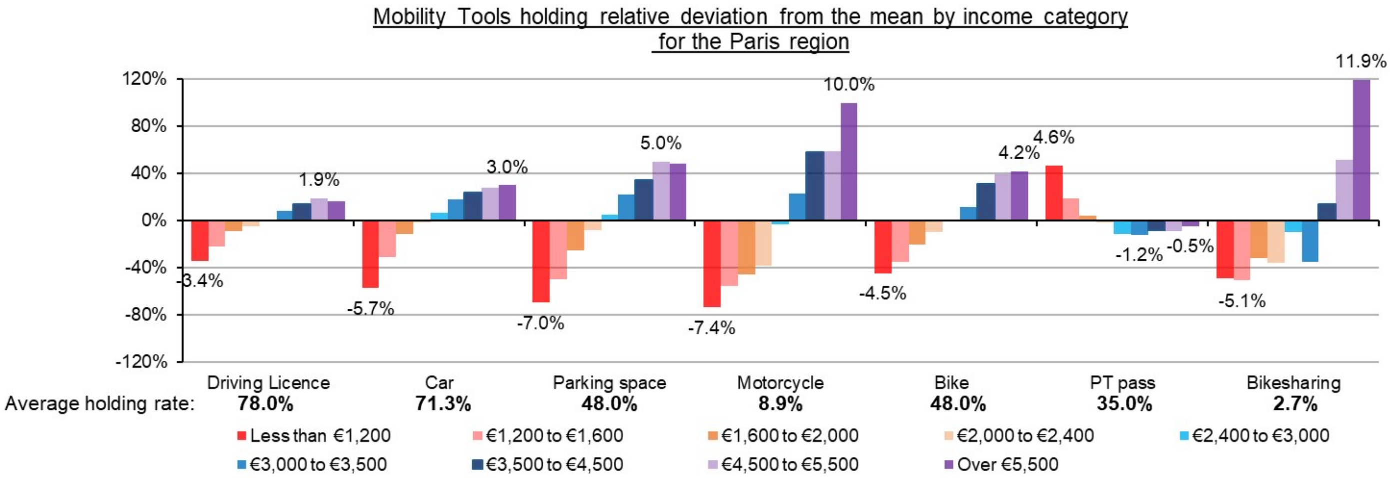


Figure 4.8 – Mobility tools holding by income group (Paris region)

To keep focusing on main socio-economic indicators, the socio-professional category and the occupation also have important effects. The data on the occupation in Appendix B shows that the active population generally has a lot more mobility tools than others except for the driving license holding which is higher for the retired. The socio-professional categories displayed in Figure 4.9 show that within the working population, the more qualification the work requires, the more individuals own a driving license. This generalization does not stand for PT and bike sharing subscriptions, even though the executive and intellectual profession is a determinant favouring mobility tools holding in general. Having a rural job diminishes the mobility tools holdings similarly with the individuals without professional activity, except for the PT pass which is often free for this last category.

These variables are often linked with an education variable measuring the highest degree reached by individuals displayed in Figure 4.10. The highest education groups seem to be more equipped than the others, and the driving license holding rate closely follows the education level. Its effect on PT subscription is less clear and the last bike sharing subscription is more held by individuals with the highest education level, which fits a rich, educated, active and male innovation-friendly population. This caricature stands as the *Vélib'* service was still new in 2010 in Paris.

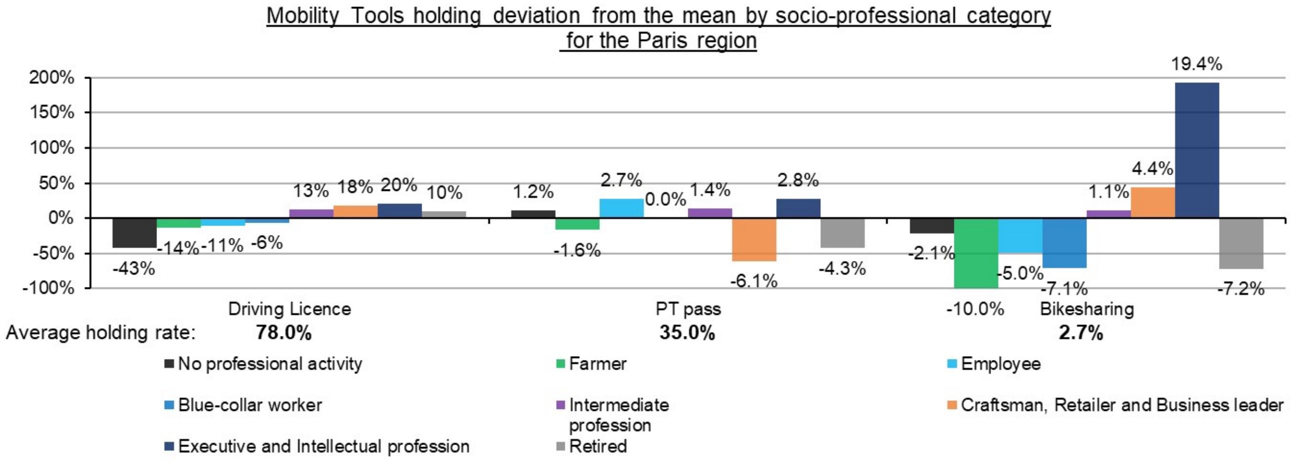


Figure 4.9 – Mobility tools holding by socio-professional category (Paris region)

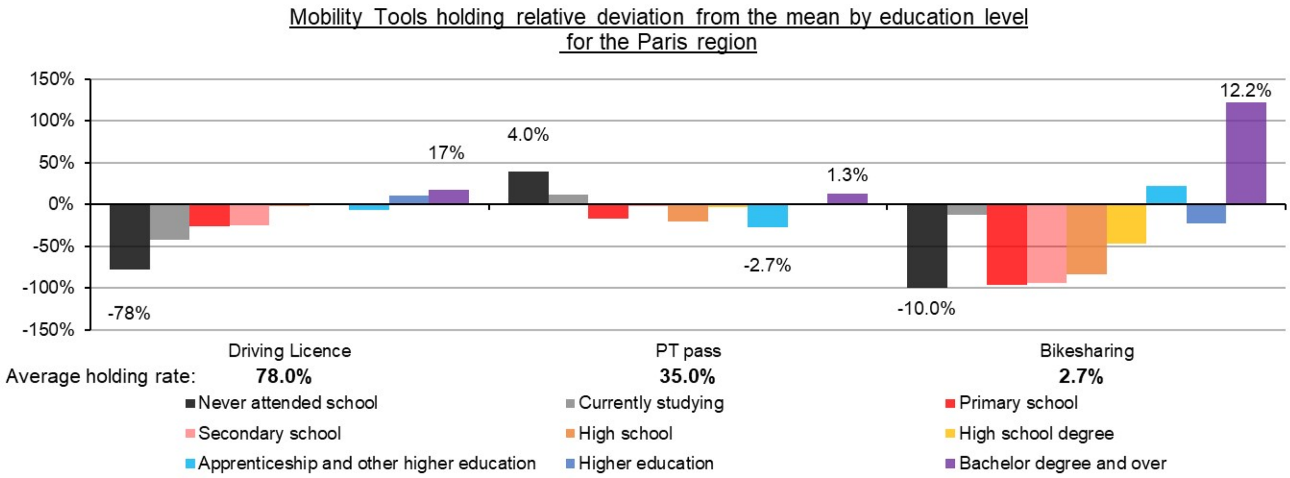


Figure 4.10 – Mobility tools holding by education level (Paris region)

These socio-economic descriptors can also be considered as a need for mobility which can be measured by looking at the average number of daily trips. While this number is directly available for individual scale mobility tools, it must be averaged over the household members for the household scale. Most mobility tools holdings do not show specific trends except for the driving license which improves from 74.1% for individuals making less than two daily trips to up to 85.2% for individuals with a high mobility need making more than 6 daily trips. The daily trips variables must also be carefully analysed because it highly depends on the way the survey is made, and especially on which day the respondents were surveyed.

4.2.4 Work-related descriptors

As suggested in the last chapter, it seems that working individuals have generally higher mobility tools holding rates. This population is characterized by strong mobility needs especially generated by constrained trips such as the home-work trip. Some features linked with workplace characteristics are proposed here for active individuals in the Paris region. The probably most important one is the workplace commune type displayed in Figure 4.11. Its effect is similar to the household location commune type which is significant: crossing both of these probably yields a lot of information on the mobility tools holding likelihood.

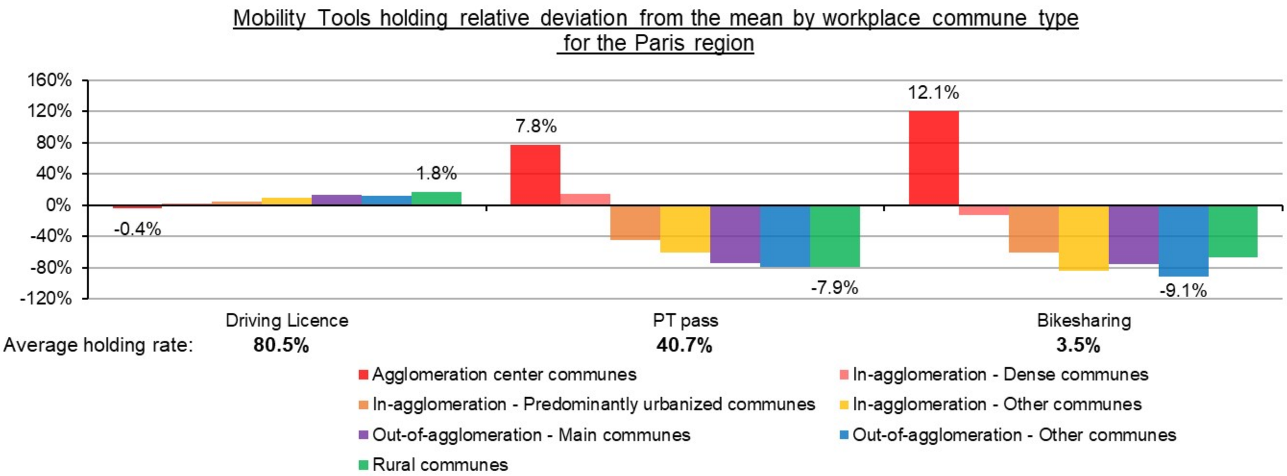


Figure 4.11 – Mobility tools holding by workplace commune type (Paris region)

The workplace unicity is also an important element framing the home-work trip because it directly relates to the mobility need. The numbers in Appendix B show that it is not especially related to driving license holding, yet it has strong effects on PT pass holding and bike sharing subscription. Indeed, having a unique out of home workplace generally rises the holding rates for both, while working from home decreases this rate as it generates a lower mobility need. There also is a high PT pass holding rate for active individuals with multiple workplaces which may come from the versatility advantage of PT.

After setting up the frame of the mobility tools holding analysis by defining its potential explanatory variables and populations, this section has highlighted main mobility tools holding socio-economic descriptors. The results are consistent with previous mobility tool analyses from chapter 3 displaying a high importance of geographic, individual and socio-professional variables on mobility tools holding. This section differentiates itself from the literature by offering analyses of seven mobility tools at the same time. But this approach is limited by the fact that some variables were only available at the individual scale and not at the household scale while household scale variables were easy to transfer to the individual scale. In order to be able to conduct a full analysis of the mobility tools and the effect of the socio-economic descriptors on their joint holding, another step must be implemented to enable the comparison of every mobility tools. The results of this step are displayed in the next section which proposes to focus on a sub-population restricted to one individual households instead of the whole Paris region population to avoid the issue of different variables scale.

4.3 Sub-population Characteristics

In order to pursue the investigation on the socio-economic descriptors of mobility tools holding, this section analyses the potential explanatory variables in a similar way as in the previous section. It follows the same descriptor study: geographical, demographic, socio-economic and work-related in turn.

4.3.1 Geographical Descriptors

The geographical variables which were already available at both the individual and the household scales still display the same behaviours such as can be seen in Figure 4.12 and Figure 4.13. The less urbanized communes they live in, the bigger the housing and if it is an individual housing, the higher the likelihood of holding a driving license, a car, a parking space, a motorcycle and a bike as opposed to a lower likelihood of holding a PT pass or a bike sharing subscription.

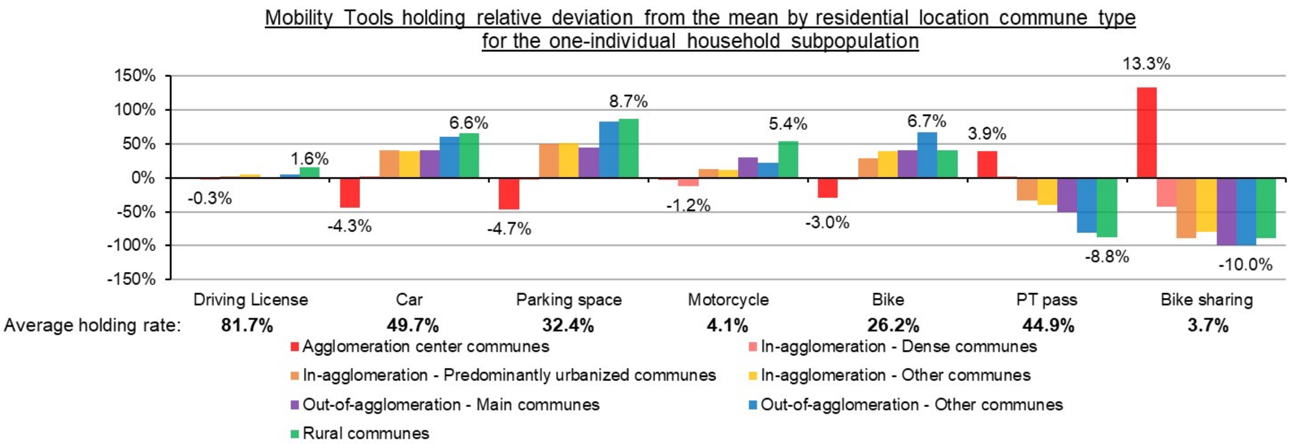


Figure 4.12 – Mobility tools holding by residential location commune type (sub-population)

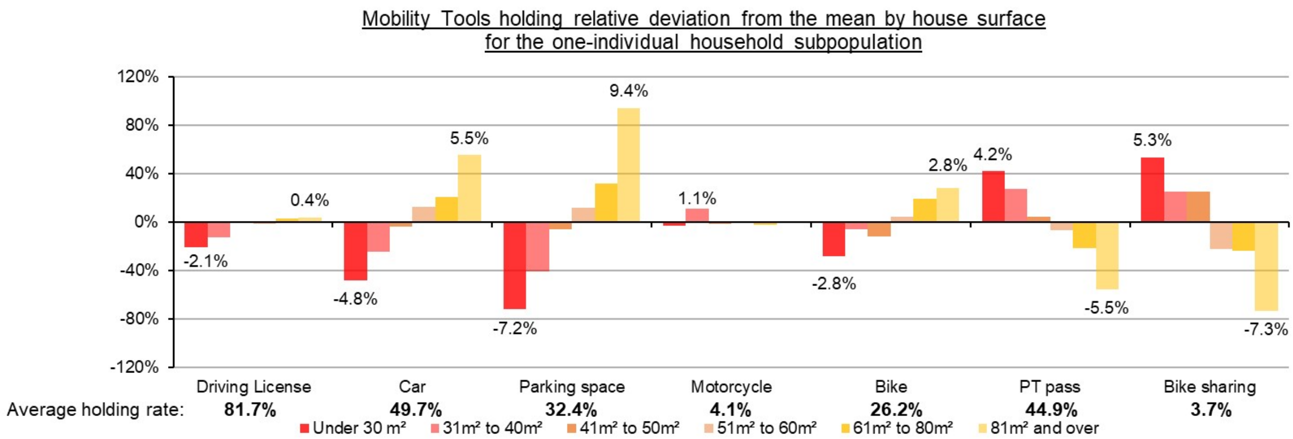


Figure 4.13 – Mobility tools holding by household surface (sub-population)

4.3.2 Demographic descriptors

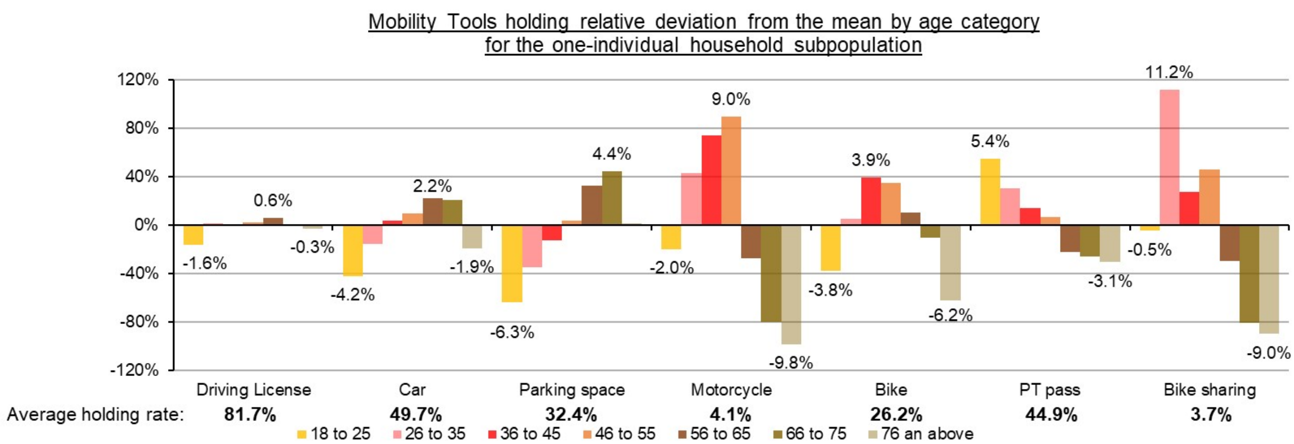


Figure 4.14 – Mobility tools holding by age (sub-population)

About the individual status descriptors, these were not available at every scale so this approach enables to get more information on their effects on several mobility tools at the same time. Figure 4.14 displays the age variable giving a more detailed information on individual mobility tools equipment than the previous household head age. The patterns displayed are similar to the household head age, with a driving license, car and parking holding increasing with age, with a small drop for the oldest population above 75 concomitant with a gender equilibrium change. Motorcycle and bike holdings show another pattern which seems to follow an inverse parabolic effect, growing quickly at first, then reaching a threshold between 36 and 55 before dropping heavily. This heavy drop is consistent with giving up these mobility tools with a diminishing physical ability to use them. Bike sharing is close to that last pattern but with an over representation of the 26 to 35 age group which probably comes from the innovation adoption effect. The final

PT subscription steadily decreases with age. To complete the individual status descriptors effect from Appendix B, the declared mobility disability and being a woman are both factors reducing the mobility tool holding shares for every studied mobility tool. Even though it was expected for the mobility disability indicator, it is surprising that being a woman still has such a negative effect, which is more pronounced for car, motorcycle, bike and bike sharing subscription holdings.

4.3.3 Socio-economic descriptors

Switching to socio-professional descriptors, the holding distributions by monthly income groups in Figure 4.15 are similar to the previous ones, with an increase for each mobility tool following an increase in income, except for the PT pass holding which is almost steady, except for the lowest income group and for the highest, but never moving more than 4% away from the average holding rate. The occupations not displayed here but in Appendix B show that on average, working is correlated with improvements of the holdings rates for every mobility tool, studying is correlated with improvements in PT pass and bike sharing subscription rates and decreases for the other mobility tools. All of the other occupations are associated with a decrease of every mobility tool holding rates, with higher effects on bike, bike sharing subscription and motorcycle holding rates for the retired population, which is consistent with the age effect analysis. Concerning the socio-professional groups displayed in Figure 4.16, all of the car-related mobility tool holdings – i.e. driving license, car and parking space – have similar patterns with higher holding rates for jobs requiring higher qualifications. It is a bit surprising for the farmer category which would be expected to be more car-dependent than others. That may be because traditional farmers are not often in one individual households, and the results cannot be significant enough to draw conclusions. Indeed, about 0.1% of the Paris population is concerned by this situation. While individuals without activity exhibit lower holding rates for individually owned mobility tools, they have average to higher holding rates for mobility services such as PT pass or bike sharing subscription. Interestingly, motorcycles seem to be favoured by average qualifications socio-professional categories.

The education variable in Figure 4.17 also brings more information on the technical background of the individuals determining their mobility tools holding choice. Generally, the higher the level of education, the higher the likelihood of holding a mobility tool, except for PT subscription which is favoured by students and individuals who never attended school. This probably comes from the social pricing giving discounts to these populations. The apprenticeship category varies a lot but

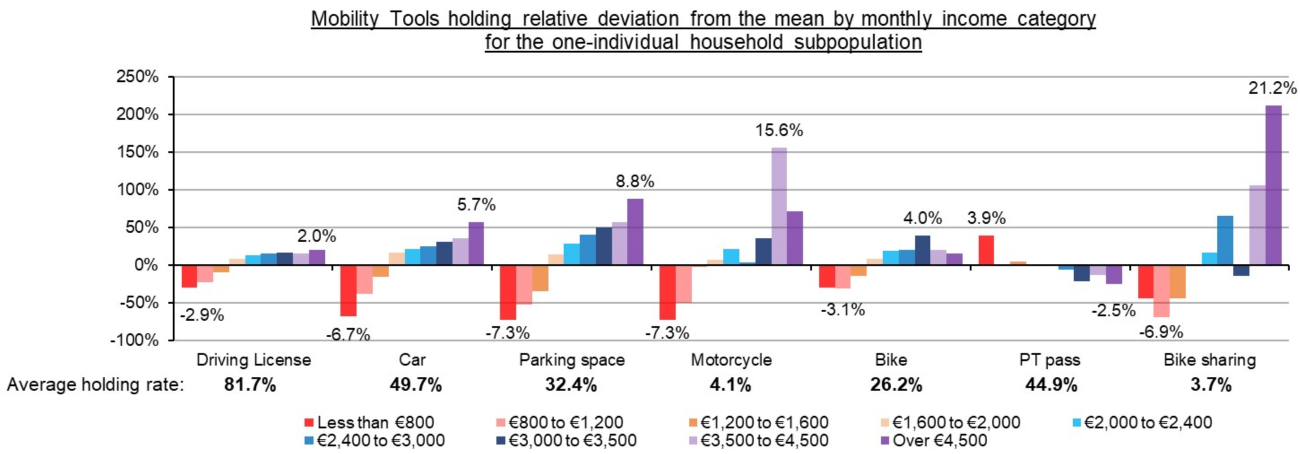


Figure 4.15 – Mobility tools holding by income (sub-population)

is not significant as there is only 0.5% of the sub-population which is in this category. Again the high positive deviation from the mean for the highest education level group suggests that it is an innovation-friendly population, and motorcycles seem to be more held by individuals with a medium level of education around the high school degree.

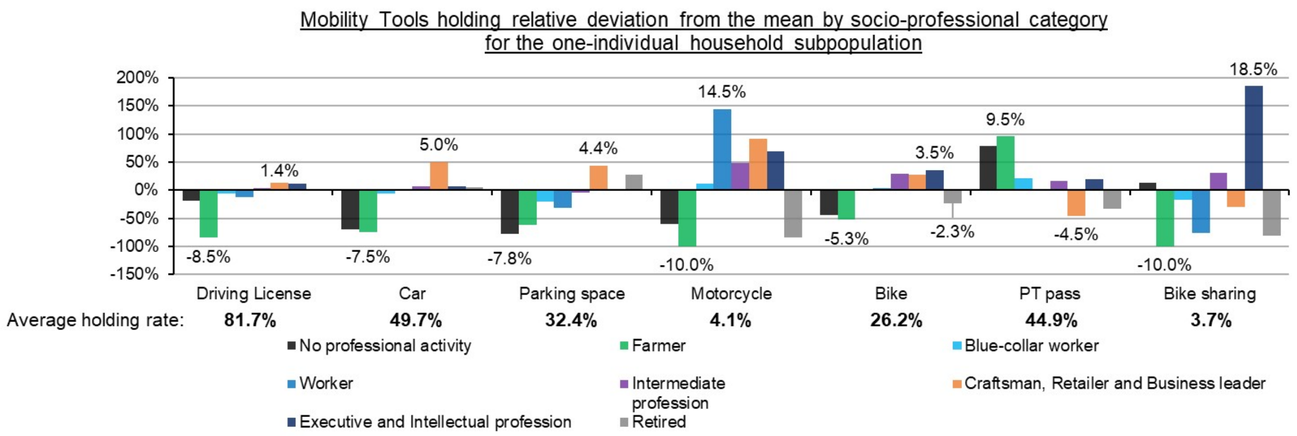


Figure 4.16 – Mobility tools holding by socio-professional category (sub-population)

The mobility tool by daily trip number pattern in Figure 4.18 is a bit troubling because it varies depending on the odd or even trip number. This variable has been tested to evaluate whether some mobility tools were more associated with high or low mobility needs. The driving license holding does not seem to react much which is consistent with its holding not being directly linked with making a trip. Making less than two daily trips is generally correlated with lower mobility tools holdings, while making more than six daily trips is correlated with private vehicle holding. Mobility services subscription seems to be more held by the individuals making more than 3 trips, as an intermediate option yet also competitive for individuals

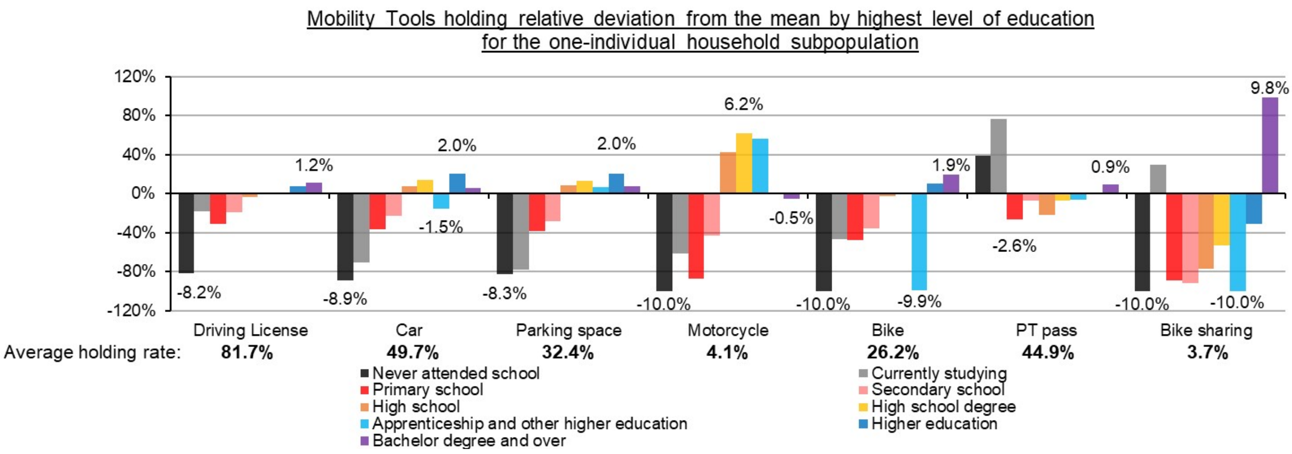


Figure 4.17 – Mobility tools holding by education level (sub-population)

with the highest mobility needs. This pattern is interesting as mobility services are usually more versatile in a sense that they do not require to carry the same vehicle over the day. This versatility is probably challenged by the possibility that PT users are more likely to centralize their activities on a few places, limiting their trip number, while vehicle holders do not need to do it and are more likely to make several small trips. A study of the trip lengths and travel times could test this hypothesis.

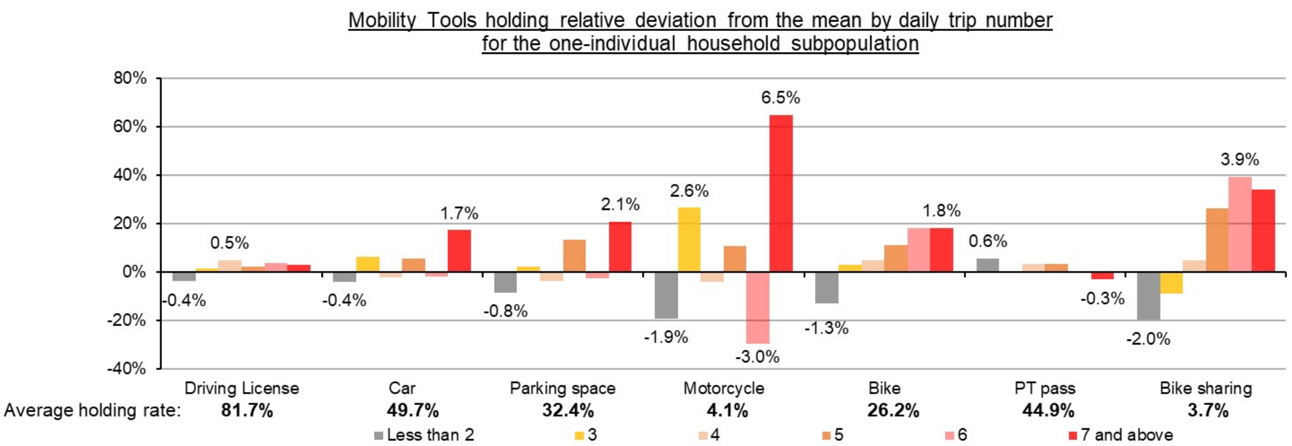


Figure 4.18 – Mobility tools holding by daily trips made (sub-population)

4.3.4 Work-related descriptors

Last, focusing on the working and studying sub-population and the effect of the workplace or study place location gives information on the end-side of the constrained home-work/study trip. Figure 4.19 displays this relationship for each mobility tool studied. The effect is similar with the effect of the household location, and even the deviations from the mean are comparable. This supports the idea that the end-point location of a regular trip is almost as important on the mobility tools holding than the home location. So looking at both ends already gives a lot of information on the mobility tools holding likelihood. Generally, private vehicles are more held by individuals who need to reach less urbanized communes while mobility services are more held by individuals who need to reach more urbanized communes, and more specifically the city centre for the bike sharing subscription. Looking at the unicity of the workplace location, it seems that most of the mobility tools holding are favoured by a unique out-of-home workplace, except for motorcycle holding which is deteriorated by it. At the opposite, working only from home is negatively correlated with every mobility tools holding, with a minimum negative relative deviation from the mean of about 7.7%, except for motorcycle holding which is more held by 22.7%. Not having a unique workplace is also a significant element statistically favouring motorcycle holding while diminishing PT pass and bike sharing subscription. These observations seem to position motorcycle holding as the most versatile mobility tool. But mobility services seem to be less held by individuals needing higher mobility versatility on their home-work trip. Car and bike parking availability at the workplace are both positively correlated with private vehicle holding while negatively with mobility services subscription.

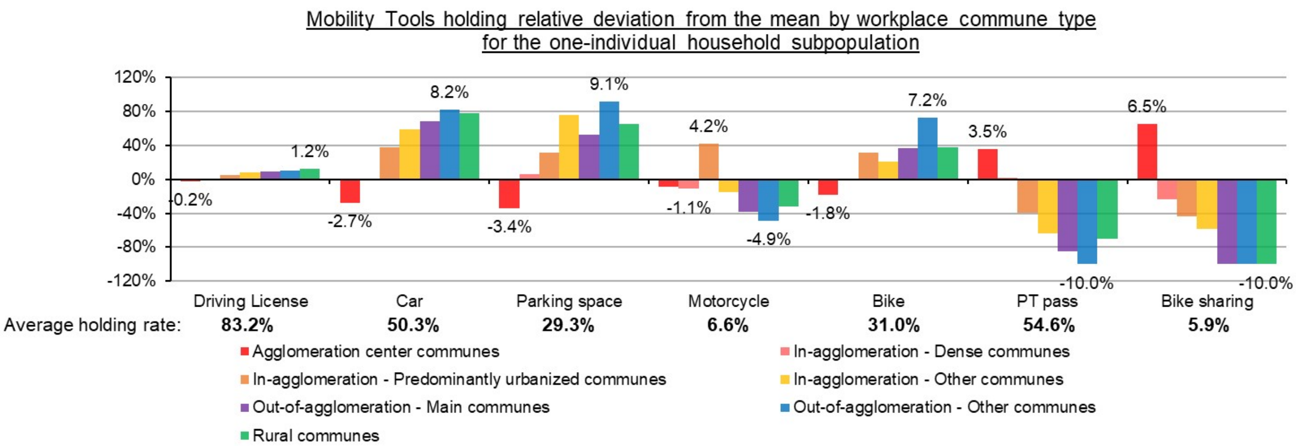


Figure 4.19 – Mobility tools holding by workplace commune type (sub-population)

This section has contributed to the dissertation by setting up a new analysis scale on a one individual households sub-population in order to solve issues of multi-scale holdings and household decisions structure. The results are mostly consistent with the previous mobility tools holding analysis from this chapter's second section, yet they are more complete thanks to lifting the multi-scale issue. The interest of geographical, individuals, socio-professional and workplace descriptors has been emphasized and confirmed, and it seems that several classifications of mobility tools are emerging from this first statistical analysis step. First the structural opposition between private vehicles holding and mobility services subscriptions appears among different holding variations along the same explanatory variables. Second, an opposition between accessible mobility tools and motorcycle, bike and bike sharing subscription mobility tools requiring better physical abilities to be used is put forward. In 2010, bike sharing subscription was statistically more favoured by the early-adopter population mostly made of young active or student men with high education level. Up until this point, the analyses remain very exploratory as they deal with mobility tools one after the other. The next section aims on improving the analysis by adding other dimension levels through correlation and multiple holding patterns analyses.

4.4 Correlation and Multiple Holding Patterns

As announced in the previous sections focusing on the effects of individual socio-economic descriptors on mobility tools holding, this section deals with multiple holding patterns. It shows the general holding interactions among mobility tools. In order to explore these interactions, several methods are used to conduct a cross-holding analysis. First, the most standard one is the correlation analysis enabling to assess co-holdings relationships. Then a decision tree representation is presented, enabling to get a glimpse at multiple holdings analysis. Last, triple diagrams of mobility tools enabling analyses of three mobility tools holding dimensions are also presented. These statistical and representation analysis tools are not exhaustive, but they are graphically intuitive and their diversity enables getting a better understanding of mobility tools holding structure and relationships.

4.4.1 Correlation analysis

Correlation analysis is a standard statistical tool. It is widely used thanks to its ability to quantify the degree of statistical similarity between two variables. Its interpreting is generally easy, a positive correlation tells that two variables have similar linear behaviours, a negative correlation tells that two variables have opposite linear behaviours, and a null correlation tells that there is no direct linear relationship between the two variables. The higher the correlation value, the stronger the statistical link is. This correlation analysis is easy to implement and quickly gives access to co-holding patterns for the mobility tools holding study.

But this indicator has some limits which must be acknowledged, especially because they often are neglected. Aside the traditional misunderstanding between statistical correlation and causality considering that any high statistical correlation implies a causal link which is the result of pure mathematical reasoning without accounting for field experience, the mathematical construction of the correlation index is also often over interpreted. Indeed, the correlation index should rather be called the linear correlation index because it is built on linear relationships. For the case when two variables have a linear relationship, they will have high correlation indexes, but it is not the case for non-linear relationships. For instance, a variable having a parabolic relationship when following another reference variable would not yield a good correlation index value while there could exist a strong parabolic causality relationship between the variable and the reference variable. Non-linear transforming is often used to avoid this issue, but doing so increases the risk of over fitting the data by designing dedicated mathematical relationships not describing a true causality pattern.

The discussion about finding an efficient indicator of the relationship between variables goes well beyond the scope of this research and is and has been addressed by many statisticians. Concerning the specific use of the correlation index for this mobility tools holding application, the mobility tools holding variables are Boolean so there is no linearity issue, which makes the use of this index even more appropriate. The results of the correlation analysis for the sub-population of one individual households is displayed in Figure 4.20 and Figure 4.21. Similar analyses have been conducted on the active sub-population and are presented in Appendix B. All of these analyses have been conducted with the R software, and some involve the use of the *corrplot*[3] package.

The correlation matrix from Figure 4.20 displays the correlation indexes weighted by the sub-population individuals. As expected, the car holding and parking space holding variables are very correlated because a parking space holding is only possible when a car is held. The car and driving license holding variables are also well correlated because holding a car requires holding a driving license to be able to use it. Along this main car-use correlation group joining car holding, parking space holding and driving license holding, bike holding is also positively correlated with these car-use tools even though displaying a weaker correlation value. This seems to imply a secondary private vehicle group aside the car-use mobility tool group. The PT pass holding variable displays a strong negative correlation value with the car holding variable and more generally with the car-use mobility tool group, suggesting an opposition between these. The bike sharing variable is not often positive so it displays very low correlation indexes. Yet it seems to be positively related to PT pass holding and driving license holding while negatively related to

[3]`https://cran.r-project.org/web/packages/corrplot/corrplot.pdf`

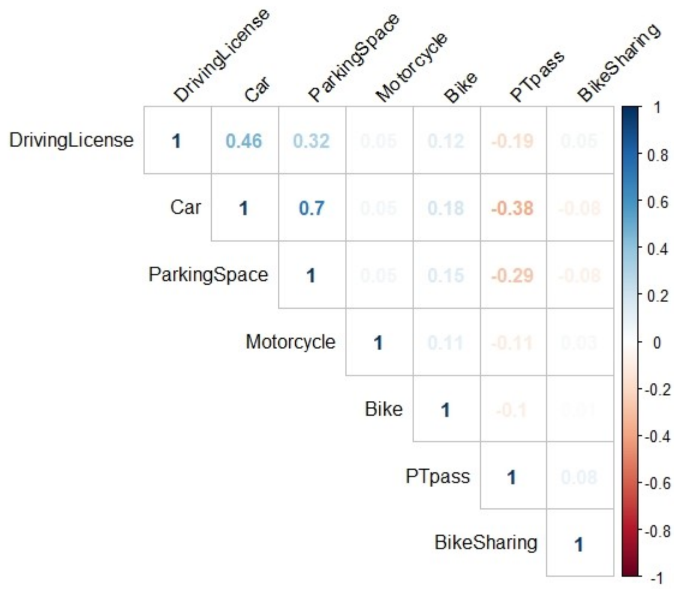


Figure 4.20 – Weighted correlations matrix of mobility tools holding for the sub-population

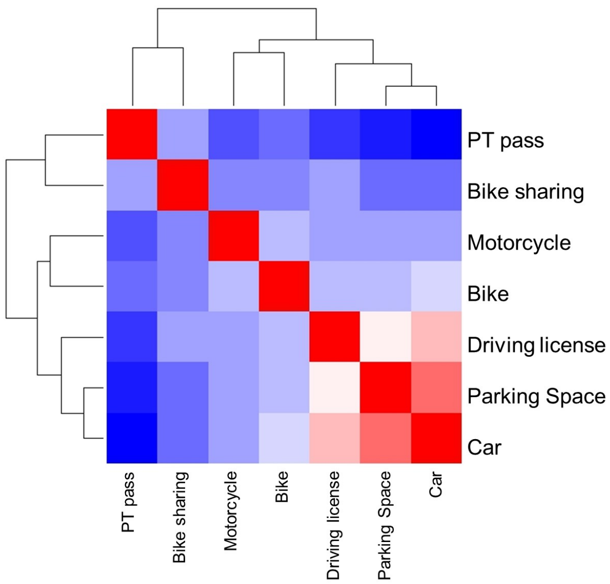


Figure 4.21 – Weighted correlations distance matrix of mobility tools holding for the sub-population

car holding and parking space holding. A strong negative correlation would have been expected between bike sharing subscription and bike holding because both are intuitive substitutes to one another, but this relationship does not appear here.

The patterns first identified from the correlation matrix are better highlighted by the correlation distance matrix in Figure 4.21. This representation considers correlation indexes as distances: a perfect positive correlation with a correlation index at 1 is considered as a 0 distance value. Then the further from 1 the correlation index is, the higher the distance, up to -1. It gives a new distance correlation matrix displayed here. The variables are also reordered to display the closest ones by one another. Red cases represent small distances while blue ones represent long distances. The correlation diagonal is made of distances 0 so it is in full red. The lowest correlation value being between car and PT pass holding, it is in full blue, and both mobility tools are at opposite sides of the matrix. In addition to this matrix clearly displaying an opposition between car-use mobility tools and the others, distance lines are available. These join the mobility tools according to their correlation distance between each other. The closest ones are joined, and then their average distance to the others is computed. This processing enables to have a better level of detail for analysing correlation groups. A general opposition between private mobility tools and mobility services first appears with the gap between PT and bike sharing subscriptions, and the other mobility tools holding. Then, within the private mobility tools group, a distinction between cycle-based mobility tools and car-use mobility tools appears too. Last, the driving license car-use mobility tool seems to be the less integrated car-use mobility tool, which may come from its special status different than the others: it does not incur holding maintenance and use costs while the others do, so it can be held without being used.

The same results appear with very small correlation value differences for the active sub-population. These results confirm the conclusions from the last section suggesting the existence of mobility services versus private vehicle groups and motorcycle and bike group versus car-use group within the private vehicle group. The remaining part of this section gives different views of these multiple holding relationships in order to confirm these first observations and identify other trends.

4.4.2 Decision tree analysis

The decision tree representation is a common one in choice and risk analysis. The principle is to start from a reference point, then to add an event box. From this box, the way is separated among the different event outcomes. Then a second event appears for each first event outcome, leading to second event outcomes and so on. For the current application, a mobility tool holding is considered as an event with two values: either the individual has the mobility tool or it has not, limiting the number of outcomes to two. So for each mobility tool holding event, only two outcomes are available. The holding outcome is systematically represented in green above the no holding outcomes in red, with a bold arrow when the outcome happens for more than 60% of the choice-making population, and a thin arrow when the outcome happens for less than 40% of the choice-making population to highlight the most chosen alternatives. The shares of the overall sub-population are represented above the event boxes. An example of a decision tree for the four most held mobility tools is displayed in Figure 4.22.

The decision tree representation is useful for displaying decision structures because it highlights the most chosen decision based on previous choices outcomes. So it is an efficient candidate representation for understanding a choice structure. It also enables to identify specific choices highly dependent from previous choices outcomes, making a niche market. The main issue here is when numerous choices are included, highly increasing the number of tree branches which makes the choice process less understandable. The decision tree also relies on the succession of choice events and different successions will yield different outcome shares because the choice events account for previous choices outcomes. So the numerous choices issue is even more complex. The choice outcomes with very low shares are generally to be avoided because they are even more spread out within a decision tree, or they should be put at the beginning of the tree. That is why the example in Figure 4.22 displays one decision tree with four mobility tools out of the seven considered, from the most held one to the least held of the four.

The example shows clear results: Focusing on the upper branch of the 81.7% sub-population equipped with a driving license, only 60% of these holds a car which is not that much considering that driving licenses are held in order to be able to use a car. The remaining 40% are then previous car drivers or occasional car drivers not driving a car on a daily basis. While holding a driving license and a car is often associated with not holding a PT pass for 74,4% of these, it is the reverse for driving license holders not holding a car with a 62.8% holding share. The bike never is the most preferred choice alternative in this decision tree, yet it seems to be more linked with car and driving license holding because the no holding shares are less important at about 65% against about 80% for the other cases.

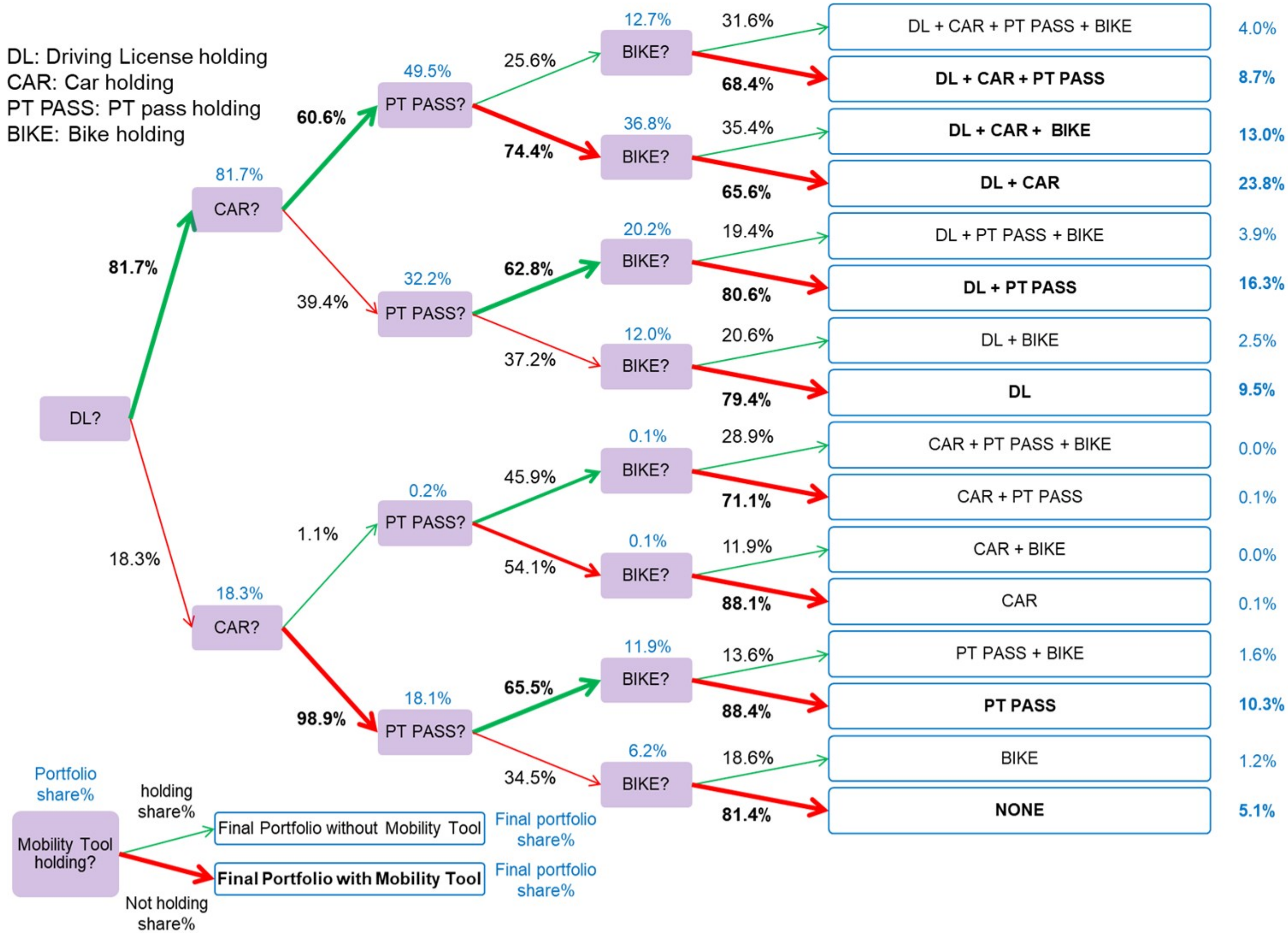


Figure 4.22 – Decision tree example with the four most held mobility tools for the sub-population

On the other tree branch for the sub-population without driving license, almost none of these has a car which makes sense. The few 1.1% holding a car are probably drivers who lost their driving licenses after police or justice decisions, car collectors who do not drive their cars, or individuals living in a household where the driving license holder is absent. The share of driving license without a car holders equipped with a PT pass is almost the same as on the other branch without driving license but slightly higher at 65.5% against 62.8%, suggesting that holding a driving license does not change much the result of the PT pass holding decision. Not holding a driving license and a car only describes 0.2% of the sub-population and cannot be used to draw general conclusions. Anyway, not holding a driving license seems to be a negative indicator for bike holding.

The decision tree representation contributes to the mobility tools multiple holding relationship by giving a detailed picture of the relationships among the mobility tools holding. Yet it suffers from its high precision by not enabling to study too many mobility tools at the same time. The application on the four most held mobility tools has revealed that holding a driving license does not seem to have as much impact on car holding as it would be expected considering the causal link between these mobility tools, and that it also has little effect on PT pass holding. Yet holding a car clearly goes against PT pass holding, and holding a driving license is a pre-requisite for car holding. Overall bike holding is not selected much, indicating that it is not often held by individuals within the sub-population, but it still is more chosen by driving license and car holders than by other individuals. This results follow the more general trend identified by the socio-economics descriptors effects and by the correlation analysis, with more detail.

4.4.3 Three mobility tools diagrams analysis

The previous decision tree representation enables studying statistical chains effects. The next representation described here displays the cross-effect of holding three mobility tools together, graphically increasing the correlation analysis dimension to three. This representation is inspired by the traditional sustainable development diagram crossing economic development, social inclusion and ecology. The triple diagrams of mobility tools follow this principle and highlight the shares of each crossing areas in the sub-population. The results are displayed in Figure 4.23.

Seven mobility tools are studied in this dissertation, but only three can be drawn on the same logical diagram, so several combinations are studied in turn. Six main combinations have been selected in this analysis: the "Top 3", the "Traditional", the "Green / Services", the "Vehicle", the "Car equipments", the "Mobility Tool Type" groups. The first one deals with the three most observed mobility tools in the Paris region – i.e. driving license, car and PT pass –, the second one deals with the most studied mobility tools in the literature – i.e. car, PT pass and bike –, the third one deals with the greenest mobility tools – i.e. PT pass, bike sharing subscription and bike –, the fourth one deals with the private vehicle mobility tools – i.e. car, motorcycle, bike –, the fifth one deals with the car mobility tools linked with the car use – i.e. car, driving license and parking space –, the sixth and last one about the mobility tool type subdivision – i.e. mobility services, motorized vehicles and non-motorized vehicles –. This panel is not exhaustive but covers a range large enough to characterize the main mobility tools.

First looking at the Top 3 diagram, almost all of the sub-population is represented as only 6.3% of the sub-population does not own any of the Top 3 mobility tools. While PT pass and driving license can be held on their own, car holding is almost always associated with driving license holding. There is a high share of threefold holding at 12.7%, and more than three quarters of the sub-population holding a PT pass also holds a driving license. These observations highlight that driving license holding is quite spread out in the sub-population and that it can be held with both the two other mobility tools. It seems that it is a very versatile mobility tool compatible with the other ones, even though it is conceptually associated with car use. The opposition between PT pass and car holding also appears because less than a quarter of the PT pass holding and of the car holding sub-population holds both a car and a PT pass.

The Traditional combination covers a smaller share of the sub-population with a 14.6% rate of unequipped individuals. While 17.0% of the sub-population holds both a car and a bike, only 9.5% holds a PT pass and bike, illustrating that bike holding is more associated with car holding. Interestingly, the bike is not often held on its own and is rather held with another mobility tool for more than eight cases out of ten. This implies that it is mostly held in combination with another mode, or that bike is used for leisure instead of travelling only. The opposition between PT pass holding and private vehicle holding appears again here, with a low sub-population share holding the three studied mobility tools at 4.0%, and a high PT pass holding only share at 26.5%.

The Green / Services is less represented in the sub-population than the previous ones because it deals with 62.4% of it. Within these, about a half holds a

PT pass only, a quarter holds a bike only, an eighth holds both a PT pass and a bike, and the remaining is made of combinations with bike sharing subscriptions. Clearly, bike sharing is more held by PT pass holders than with a bike or by itself, while both PT pass and bike mobility tools are more held on their own. This is consistent with bike sharing being a mobility service complementary with the PT, and in opposition with bike holding. Individuals holding a bike sharing subscription and a bike probably have a bike dedicated to leisure only or are transitioning to bike use and still have a bike sharing subscription.

The fourth diagram about Private vehicles deals with the lowest sub-population share with 40.1% not holding any of these. The car is the only private vehicle mobility tool standing more on its own rather than held with other vehicles. Bikes are more held with a car than by themselves and motorcycles too. Interestingly, motorcycles are more held with the two other vehicles, suggesting that it might be an additional vehicle used for leisure or in addition with another vehicle. The private vehicle characterization seems to be quite consistent and framed around car holding.

The Car equipments diagram is less diverse because most of it is based on driving license and car holding, which are both prerequisites for car use. It shows again the bias of parking space holding variable because it cannot indicate parking space holding without car holding. Yet it must be noticed that most of the car held without driving licenses are combined with a parking space holding, strengthening the hypothesis that these are mostly collector cars or cases for which the car is not driven and stored in an owned parking space. The high share of almost a third of the sub-population holding driving licenses without a car is striking and characteristic of a city where some individuals hold a driving license in order to be able to occasionally use a car, but not to use it on a daily basis. Also, almost two thirds of the car holders also hold a parking space, and this share is slightly underestimated because of the parking space variable lack of accuracy.

The last diagram has been built by considering the observed private vehicle versus mobility services opposition, and by differentiating motorized and non-motorized vehicles. This representation is versatile and enables distinguishing mobility tools groups: the distinction between mobility services and private vehicles is clear because most mobility services are held without private vehicle, and only 4.2% of the sub-population holds all of the studied mobility tools. The non-motorized vehicle distinction does not stand much as most of the non-motorized mobility tools are held with motorized mobility tools. With a few percentage differences, this dia-

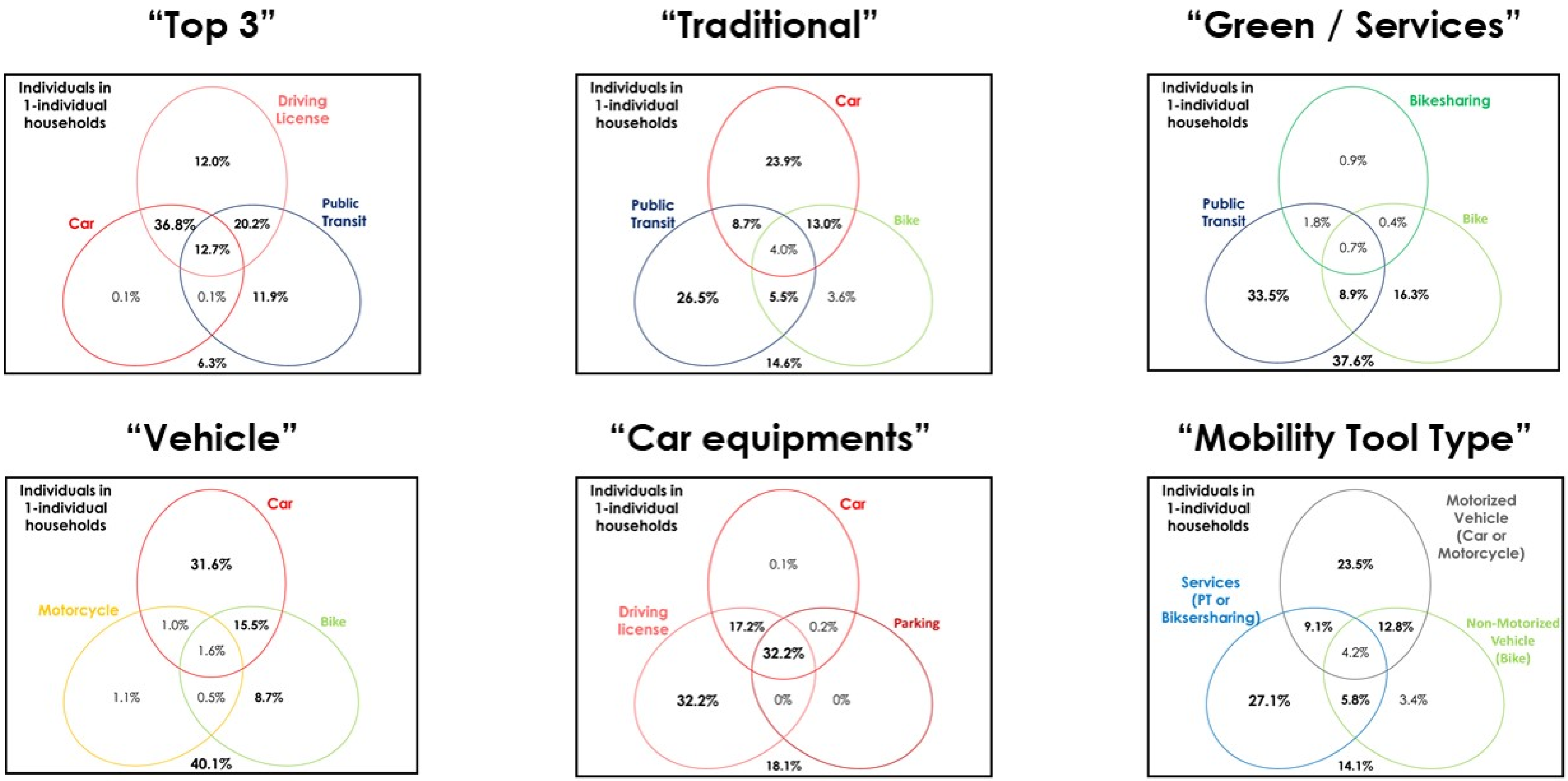


Figure 4.23 – Triple diagrams of mobility tools holding for the sub-population

gram is very similar with the Traditional mobility tool combination diagram.

The level of detail of this diagram approach is better than with the former correlation analysis and has shown its ability to give a much finer description of the multiple mobility tool holding description. Yet it is less usual and less statistical tools are available to study it. It has again highlighted the mobility services opposition against private vehicle, but given more information on the bike sharing, bike and motorcycle status within these. Indeed, it seems that the main mobility tools holding frame is still built around the car opposition against PT pass holding, with additional secondary mobility tools gravitating around. The bike sharing subscription is a tool complementary with PT subscription while motorcycle and bike holding are complementary with car holding. As expected, driving license holding appears to be a prerequisite to car holding, but does not much determine car or PT pass holding and seems to be compatible with every mobility tool holding.

When the socio-economic descriptor effects analysis has enabled to highlight potential explanatory variables for mobility tools holding, this section has focused on multiple mobility tools holding effects. The first widely spread statistical correlation analysis has characterized effects between mobility tools and has identified mobility services versus individual mobility tools and individual car-based versus individual cycle-based mobility tools oppositions. The statistical chain displayed in the decision tree representation has given more information to assess that driving license holding is a prerequisite for car holding but not really a determinant, and that bike holding is associated with driving license and car holding. The last triple diagram approach has enabled to study three mobility tools holding at the same time, and to confirm the previous observations, while giving details on the mobility services versus individual mobility tool opposition which is rather built on a PT pass holding versus car holding opposition with complementary bike sharing subscription, and motorcycle and bike holding mobility tools. These different approaches are converging toward a same general picture the mobility tools holding structure and could be used as an input for mobility tools choice models design for the sub-population.

4.5 Portfolio Analysis

The previous sections have dealt with the issue of multiple mobility tools holding from a mobility tool perspective. This section switches of perspective to display a portfolio perspective. Instead of considering the mobility tool as the analysis unit, this approach takes the mobility tools portfolio as a new unit with different characteristics. This approach is the most complete one, yet it is difficult to apply when considering too many mobility tools because each added mobility tool doubles the number of individual portfolios. When seven mobility tools are considered in this analysis, it is not possible to analyse the effects of socio-economics variables on each of the 128 possible portfolios. Yet, this section first describes the mobility tools portfolios to better know their spread in the sub-population. Then a comparison of the active sub-population and retired sub-population is made because these are the two main sub-population groups observed. Last, a mobility tool perspective within the portfolio set up is reproduced to better understand the different mobility tools combinations for each of the seven cases.

4.5.1 Mobility tools holding portfolios in the sub-population

Table 4.4 shows the overall portfolio ranking, from the most represented portfolio in the Paris region sub-population to the least represented one. Grey lines are implemented when reaching the 50.0%, 90.0%, 95.0%, 99.0%, and 99.9% thresholds. For the sake of readability, this table has been truncated in order to avoid a too lengthy data set and to represent more than 99.0% of the sub-population. The portfolio component side of the table displays a 1 when a mobility tool is within the portfolio and a 0 when it is not. The portfolio size details the number of mobility tools within the portfolio, and a difference is made between the EGT 2010 sample shares and the weighted Paris region share. The whole table is available in Appendix B.

The three most represented mobility tools portfolios correspond to the traditional opposition between car and PT: PT holding with or without driving license, and the whole car equipments holding. When focusing on the portfolios representing 55.9% of the sub-population, the maximum portfolio size is only four and five at the 99.0% threshold, showing that large portfolios are not much spread out in the sub-population. The 90.0% threshold is reached with fifteen portfolios neither displaying motorcycle holding nor bike sharing subscription, clearly showing that these mobility tools are marginal. Interestingly the null portfolio and a similar portfolio with only driving license holding characterizing a mobility restrained population are ranked eighth and fourth, together representing a 13.3% sub-population share which is quite high. The first portfolio mixing private vehicle holding and mobility service subscription is ranked seventh with a 5.1% share. This observation shows that there is a strong cleavage between mobility services and private vehicles, and a large market for linking these mobility tools categories.

For the subpopulation

Portfolio components							Portfolio size	EGT 2010 share	Paris region share	Paris region cumulative share
Driving license holding	Car holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription				
1	0	0	0	0	1	0	2	12.5%	14.9%	14.9%
1	1	1	0	0	0	0	3	15.7%	14.8%	29.6%
0	0	0	0	0	1	0	1	9.1%	10.0%	39.6%
1	0	0	0	0	0	0	1	7.1%	8.4%	48.0%
1	1	1	0	1	0	0	4	9.8%	7.9%	55.9%
1	1	0	0	0	0	0	2	8.7%	7.9%	63.8%
1	1	1	0	0	1	0	4	5.5%	5.1%	68.9%
0	0	0	0	0	0	0	0	4.4%	4.9%	73.8%
1	1	0	0	1	0	0	3	4.3%	3.6%	77.3%
1	0	0	0	1	1	0	3	2.9%	3.3%	80.6%
1	1	0	0	0	1	0	3	3.3%	3.1%	83.7%
1	1	1	0	1	1	0	5	2.7%	2.3%	86.0%
1	0	0	0	1	0	0	2	2.0%	2.1%	88.2%
0	0	0	0	1	1	0	2	1.4%	1.6%	89.7%
1	1	0	0	1	1	0	4	1.6%	1.4%	91.2%
1	0	0	0	0	1	1	3	1.0%	1.2%	92.4%
0	0	0	0	1	0	0	1	1.2%	1.0%	93.4%
1	1	1	1	1	0	0	5	1.2%	1.0%	94.4%
1	0	0	1	0	0	0	2	0.5%	0.6%	95.0%
1	1	1	1	0	0	0	4	0.6%	0.5%	95.5%
1	0	0	0	0	0	1	2	0.3%	0.5%	96.0%
1	0	0	0	1	1	1	4	0.4%	0.4%	96.4%
1	1	0	1	1	0	0	4	0.4%	0.4%	96.8%
1	1	0	1	0	0	0	3	0.3%	0.3%	97.1%
0	0	0	0	0	1	1	2	0.2%	0.2%	97.3%
0	0	0	1	0	0	0	1	0.2%	0.2%	97.4%
1	0	0	1	1	0	0	3	0.2%	0.2%	97.6%
1	1	0	0	0	0	1	3	0.2%	0.2%	97.8%
1	1	0	0	0	1	1	4	0.2%	0.2%	98.0%
1	1	1	0	0	0	1	4	0.2%	0.2%	98.2%
1	0	0	1	1	1	0	4	0.1%	0.2%	98.3%
1	0	0	1	0	1	0	3	0.1%	0.1%	98.5%
1	1	1	1	0	1	0	5	0.2%	0.1%	98.6%
1	1	1	0	0	1	1	5	0.1%	0.1%	98.7%
1	1	1	0	1	0	1	5	0.1%	0.1%	98.8%
1	0	0	0	1	0	1	3	0.1%	0.1%	98.9%
1	1	0	0	1	1	1	5	0.1%	0.1%	99.0%

Table 4.4 – Main mobility tools portfolios in the sub-population

		Subpopulation	Active Subpopulation	Retired Subpopulation
Average portfolio size		2.43	2.67	2.27
Minimum number of portfolios representing a population share above:	50%	5	5	3
	90%	15	18	10
	95%	20	24	12
	99%	37	43	18
	99.90%	56	57	29
Number of different portfolios held		62	61	32
Null portfolios (driving license only or no mobility tool)	share	13.3%	5.6%	23.0%
	rank	4th and 8th	10th and 12th	2nd and 6th
Full portfolio (every mobility tool)	share	0.045%	0.036%	0%
	rank	49th	57th	Not held

Table 4.5 – Sub-population, active sub-population and retired sub-population portfolios characteristics

Overall, sixty-six portfolios were not held within the sub-population, and the full portfolio encompassing all of the seven mobility tools studied is not much held, at the forty-ninth rank by 0.04% of the sub-population.

4.5.2 Portfolio patterns among the active, retired and whole sub-population

While the sub-population is mostly characterized by a combination of active and retired individuals, it is relevant to investigate whether these main two groups representing the major part of the sub-population have similar trends. It is also useful to study the active sub-population to understand the effect of a constrained home-work trip on the mobility tools portfolios. In order to avoid comparing three big tables similar to Table 4.4, Table 4.5 summarizes the data of these tables fully displayed in Appendix B.

Table 4.5 shows that on average, the active sub-population has larger portfolios than the retired sub-population, both around the sub-population portfolio average size at 2.43. This observation is intuitive because the active sub-population is expected to have higher mobility needs than the retired sub-population. It displays a polarization of the sub-population between these two groups. The active sub-population also has higher or equal portfolios within each threshold value and overall than the sub-population, and a lot higher when compared with the retired sub-population. This means that the active sub-population has a higher portfolio diversity while the retired sub-population individuals do not have many different portfolios. It may come from the younger age of the active sub-population showing mobility longitudinal behavioural evolution, or from more similar mobility needs generating similar mobility tools portfolio demand for the retired sub-population. When looking at the null portfolio share and ranks, it appears that it is well represented within the retired sub-population and about four times less represented in the active sub-population. So when the active sub-population has diverse portfolios with higher average portfolio size and a low number of null portfolios, almost a quarter of the retired sub-population has a null portfolio while it also has much less diverse and much lower size portfolios. The full portfolio is almost not held in the sub-population, which probably comes from the high number of mobility tools encompassed here. When looking at the mobility tools portfolios in Appendix B to get more detail on these results, the top 5 portfolios are roughly the same among the three sub-populations, but the first portfolio mixing private vehicle and mobility services mobility tools is the sixth one for the active sub-population while it is the eighth one for the less diverse retired sub-population. It is also striking that almost a quarter of the retired sub-population holds the same car equipment portfolio.

4.5.3 Portfolio analysis by mobility tool

Now that an overview of portfolio holdings in the sub-population is made, investigating portfolios including a specific mobility tools give information on the most common mobility tools combinations with this specific mobility tool. In order to make this analysis, tables similar with Table 4.4 are built for each mobility tool. These tables consider portfolios encompassing the specific mobility tool studied, so the portfolio components side only describes the other mobility tools holding and the portfolio size can not be under 1. These tables are fully available in Appendix B and Table 4.6 gives summary statistics to ease the interpreting of these lengthy tables like Table 4.5 for the general, active and retired sub-population.

		Driving license holding	Car holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription
Average portfolio size		2.78	3.32	3.66	3.72	3.46	2.48	3.33
Minimum number of portfolios representing more than:	50% of the mobility tool's holders	4	3	2	3	3	2	3
	90% of the mobility tool's holders	12	8	4	13	9	8	13
	95% of the mobility tool's holders	16	10	5	17	11	9	17
	99% of the mobility tool's holders	28	21	11	22	21	18	22
	99.9% of the mobility tool's holders	41	31	16	24	29	27	24
Number of different portfolios held		44	35	17	24	31	30	24
Single mobility tool portfolio	mobility tool's holders share	10.3%	0.1%	0.0%	4.7%	4.0%	22.2%	0.7%
	rank	3/44	28/35	not held	6/24	8/31	2/30	21/24
Full portfolio (every mobility tool)	mobility tool's holders share	0.05%	0.09%	0.14%	1.08%	0.17%	0.10%	1.19%
	rank	38/44	26/35	15/17	18/24	23/31	24/30	16/24

Table 4.6 – Main mobility tools portfolios in the sub-population

Overall, the highest portfolio sizes are for the parking space and motorcycle holdings at about 3.7, and then for the car holding and bike sharing subscription at about 3.3. A high portfolio size means here that the mobility tool is not often held alone, so that it is a complementary equipment or that it requires another mobility tool to be used. With this interpreting, parking space, motorcycle holdings and bike sharing subscription are complementary mobility tools, while the car requires a driving license holding. At the opposite, driving license holding and PT holding portfolios sizes are low, under 2.8. It can be interpreted that holding a driving license does not imply any other mobility tools holding and that it can be held on its own. It is the same with the PT pass except that it also grants a full access to the PT network.

Focusing on the number of different portfolios held and the thresholds together, it is possible to state whether a mobility tool is held in several diverse portfolios or in a few portfolios. Clearly, parking space, motorcycle and bike sharing subscription portfolios appear in the lowest number of portfolios, under 25. It is logical for the parking space because it is only computed for individuals holding a car. It is all the more pronounced than it is at the same time a mobility tool complementary with car holding and not often held on its own. Indeed, motorcycle holding is often complementary held with a car, and bike sharing subscription as a complement to PT pass, limiting its diffusion in portfolios without the main mobility tool it is complementary with. To reinforce this observation, it must be observed that 95% of the individuals holding a parking space holds it in only 5 different portfolio configurations. On the reverse, 44 driving license portfolios out of 64 possible portfolios encompassing driving license holding are represented in the sub-population, making it a very general mobility tool held in several portfolios configurations.

In addition to these first statistics, the single mobility tool portfolio indicates whether the portfolio only encompassing the single specific mobility tool is well represented or not, specifying whether the mobility tool is mostly held on its own or not. The results are straightforward for the PT pass which is held in the single mobility tool portfolio for 22.2% of the PT pass holders, while the others are rather low, under 1% for most. The driving license is also often held on its own, which probably comes from the mobility restrained retired sub-population as interpreted from the analysis of Table 4.5. The bike holding case suggests that a few sub-population individuals are only relying on this mobility tool. Last, the full portfolio statistics is not very relevant here because only a few sub-population individuals hold it, and it is not recommended to draw general conclusion on such a small sample.

Looking at the detailed portfolio tables in Appendix B, interesting observations can be made on mobility tools combinations. First on the portfolios including driving license holding, it is surprising that the most represented one is the portfolio including a PT pass holdings only, for 18.2% of the individuals in the sub-population holding a driving license, closely followed by the minimum car use portfolio with a car only at 18.1%. The third most represented portfolio in the driving license holders sub-population is the single portfolio without any other mobility tool at 10.3%. So within the three most represented portfolios of the driving license holders, two do not encompass car holding which clearly means that driving license holding does not imply car holding. Motorcycle holding and bike sharing subscription only appear in small portfolios under 2% of the driving license holders, which probably comes from their low shares in the overall sub-population and Paris region population.

On the car holding sub-population portfolios side, the first striking and expected result is that 98.8% of the most represented portfolios in the car holding sub-population also hold a driving license and the single portfolio is held by only 0.1%. This makes driving license a proper prerequisite for car holding, a mobility tool which does not stand on its own. Most of the car holders – more than 60% – also hold a parking space and the most held portfolio gathering the three car equipments is held by up to 29.7% of them. This highlights a strong combination between these two. The results are less clear on motorcycle, bike, PT pass holdings and bike sharing subscription, but none of the top 90% portfolios include motorcycle holding and none of the top 95% portfolios include bike sharing holding for the car holders.

As it was built on the car variable, parking space holding only appears with car holding, and almost always with driving license holding which is a prerequisite for the former car holding. The top 95% portfolios include almost every mobility tool except for the bike sharing subscription. Overall, there are no other explicit general trend from this parking space holding variable. Motorcycle holding does not appear in the top 90% which is counter intuitive because holding a parking space would have been expected to be associated with motorcycle holding.

On the portfolios of the motorcycle holding sub-population, there seems to be no reverse relationship linking motorcycle to parking space holding, even though the most represented portfolio within this population is the full private equipments portfolio at 23.8%. It seems that motorcycle holding is often associated with driving license holding and less with car holding, and is held with a driving license for only 14.1% of the motorcycle holders. PT pass holding does not appear in the top 75% portfolios of the motorcycle holders and bike sharing in the top 90%, making motorcycle a mobility tool not much compatible with these mobility services tools.

Interestingly, the bike holding populations holds a lot of portfolios including driving license holding, then car holding. It seems to be more compatible with PT pass holding because it appears in the top 3 portfolios of the bike holders. The most represented portfolio held by 30.1% of the bike holders is the one encompassing private vehicle equipments and the single portfolio is held by 4.0% of them.

The PT pass holding sub-population displays strong patterns highlighted by the second most represented portfolio being the single portfolio at 22.2%, and by the most represented portfolio being the one with driving license holding only, quite similar with the single portfolio, for 33.2% of the PT holders. So the PT pass is a stand-alone mobility tool confirming the analysis of Table 4.6. It seems to be especially opposite to motorcycle holding which is not well ranked in the portfolios.

Last, the focus on the bike sharing sub-population yields that it is almost never held alone because the single portfolio is represented in 0.7% of the bike sharing subscribers, and quite often with PT pass and driving license holdings. It seems to be opposite to motorcycle holding, but not that much to bike holding as it appears in the third most represented portfolio. These last results are not very significant though because the bike sharing subscription holding share is quite low.

This section brought a more detailed analysis by portfolio better displaying their diffusion in the population. It first studied the general portfolios, enabling to identify that the most held ones mostly opposed car holding to PT holding, and that the full portfolio was almost never held. Second, it compared the active sub-population and the retired sub-population, showing that the active sub-population has a higher average portfolio size and holds more diverse portfolios while a quarter of the retired sub-population holds the same portfolio and that the null portfolio is four times more represented in this retired sub-population. These results suggest that the sub-population is polarized between these two groups. Third, the portfolios were analysed by mobility tool, focusing on the other mobility tools combinations diffusion. These yielded that the driving license is the most diverse mobility tool held with the highest number of other mobility tools combinations in the sub-population, and that it stands well on its own. It also does not imply car holding while being a prerequisite for it. On the reverse car holding is often accompanied with another mobility tool holding and is often associated with parking space holding too. Motorcycle is also a mobility tool held with others, and seems close to the private vehicle group, but not much combined with car holding. The bike average portfolio size is high suggesting that it is a complementary mobility tool, but its association with other mobility tools is not clear. The PT pass is the most stand-alone mobility tool, most often held on its own and with the lowest average portfolio size, and seems opposite to motorcycle holding. Last, bike sharing subscription is almost never held on its own and is associated with PT pass holding.

When trying to link the portfolio analysis by mobility tool and the general portfolio analysis, it appears that the top 3 portfolios for driving license holding, car holding, parking space holding, bike holding and PT pass holding are all in the top 10 of the general portfolios, and each of the mobility tools portfolios in the top 10 of the general portfolios represent between 55% and 85% of the respective mobility tools holders – this range could be reduced to 70% to 85% without the bike –. So a general study of all of these mobility tools would be relevant if focusing on the top 10 general portfolios and specific motorcycle holding and bike sharing subscription alternatives, without other mobility tools interactions.

Conclusion

This chapter has presented several analyses of the mobility tools holding phenomenon in the Paris region.

It begun with a first section describing the survey characteristics, the seven mobility tools considered – driving license, car, parking space, motorcycle, bike, PT pass, bike sharing subscription –, their definition and their target population, and the holding scale issue solved by reducing the study population to the one individual household sub-population. This approach deals with about 20% of the Paris region adults and the sub-population is mainly subdivided between a retired and an active sub-population.

The second section displayed the effects of several socio-economic variables on the full set of mobility tools holding. In order to give a better visual description, relative deviations from the mean have been used as they enable to better understand mobility tools holding variations. The same socio-economic descriptors as for the second section were studied in the third section, but on every study mobility tools. This gave more detailed information on geographic, individual condition and socio-economic variables' effect on the mobility tools holding phenomenon.

After this study of the socio-economic descriptors, the relationship among mobility tools holdings has been investigated in a fourth section dealing with multiple mobility tools holdings. The use of correlation analysis, a decision tree and triple diagrams of mobility tools has enabled to better understand the mobility tools holding structure.

In order to push this approach further, a final fifth section dealt with the mobility tools holding phenomenon by studying mobility tools portfolios. It first described general portfolios, before identifying differences between the active and the retired sub-population portfolios holdings, and analysing the set of portfolios encompassing each mobility tool to better understand their usual associations. A main take-away is that a study of the main 10 portfolios is generally large enough to study the five most represented mobility tools out of seven.

Over the chapter, several descriptive statistics tools were used. Their results seem to converge toward an overall mobility tools holding structure. First the effect of socio-economic descriptors is key, the question of the dominant socio-economic variables still remaining, because most are heavily correlated. Second the mobility tools holding structure seems to be mostly based on the opposition between car and other private equipments holding, and PT pass and other mobility services holding. Driving license holding, even though a prerequisite for car holding, does not seem to imply any other mobility tool holding. The boundary between a socio-economic indicator status and a mobility tool status is blurred for this equipment. Otherwise, the set of car equipments encompassing car holding and parking space holding seems to differentiate itself from the motorcycle and bike holdings requiring more physical ability. The study of motorcycle holding and bike sharing subscription is difficult because both were not much represented in the Paris region population and would probably require dedicated surveys. But it seems that the bike sharing subscription mobility tool can be approached as a new technology – which was the case in 2010 – adopted by an early-adopter population, complementary with PT pass holding, and not opposed to bike holding at this former *Vélib'* development stage. PT pass is a specific mobility tool because it seems to be the most stand-alone alternative among all of the mobility tools encompassed in this chapter. The sub-population has also revealed being polarized between the active and the retired sub-population. Indeed, the first one has large and diverse portfolios while the other one has small portfolios, and a high share of null portfolios, suggesting that dealing with each sub-population group separately may give better results.

Now that the mobility tools holding phenomenon is better understood, a next chapter modelling the phenomenon would give valuable information on the main socio-economic descriptors to consider and would enable to try to corroborate the identified mobility tools holding structure with adequate choice alternative model structures. The current chapter has also suggested that the home-work trip characteristics had strong effects on mobility tools holdings, highlighting that a model including home-work trip characteristics may be an improvement of the mobility tools choice model.

Chapter 5

Mobility Tools Holding Models for Paris

Introduction

The conceptual description of mobility tools and the statistical analysis of the mobility tools holding phenomenon have illustrated the complex structure of the phenomenon and its characterization. They also presented the seven mobility tools considered in this dissertation: driving license, car, parking space, motorcycle, bike, PT pass and bike sharing subscription. The last chapter has revealed some key correlations at the descriptive stage which can be used for representing this complex phenomenon: a strong impact of socio-economic characteristics of individuals and a mobility tools holding structure organized around private vehicle holding on one side, and mobility services subscription on another side. In order to simplify the modelling approach of the phenomenon, a sub-population of one individual households has been studied to avoid issues of mobility tools holding scales. A last result has also shown that most of the mobility tools holding happened in the ten most represented portfolios within the sub-population, enabling to reduce the number of alternatives. These elements are a starting point on which to build mobility tools holding models to further investigate the phenomenon.

The cases of two specific mobility tools require a special approach. First, the parking space mobility tool is only considered in addition with car holding in the EGT 2010 data set. So it makes no sense trying to represent parking space on its own, and it will only be considered as a possible mobility tool complementary with car holding. The second specific mobility tool is the driving license. Indeed, chapter 4 has brought elements confirming that it is different from other mobility tools as it is very diffused and represented in both the private vehicle and the mobility services main portfolios. These results suggest that it can almost be considered like a socio-economic descriptor rather than a mobility tool. But the models developed in this chapter will still consider driving license as a mobility tool to model. Last, driving license holding also is a prerequisite for car holding and the car mobility tool should not be considered without driving license.

This modelling chapter aims on expanding the previous mobility tools holding characterization by identifying the influences of the model variables, the quantitative measurement of their isolated effect followed by the quantification of their joint effect on mobility tools holding. The role of the need for mobility is also addressed with accounting for the structural effect of home-work trips on the mobility tools holding choice. The methods employed to run this modelling stage analysis directly refer to the discrete choice modelling field, and more precisely employing the logit specification. In line with the previous chapters, the models are implemented on the sub-population of the individuals living in one individual households in the Paris region and the data comes from the EGT 2010 Paris region travel survey.

In order to further the analysis of the mobility tools holding phenomenon, the current chapter first focuses on detailing the developed modelling approach involving logit discrete choice model formulations and a specific processing for active individuals subject to home-work trip constraints. It then models separate mobility tools to enable understanding the main socio-economic variables separately describing each mobility tool. Third and last, mobility tools portfolio models are built to get a wider and more detailed understanding of the phenomenon. These models bring additional information from the first statistical analyses, by determining the most important socio-economic variables to differentiate several mobility tools holdings, instead of their isolated effect on an isolated mobility tool. The portfolio model also yields information on potential co-holding effects and sets the basis for potential mobility tools holdings forecasts in the Paris region.

5.1 Model methodology and explanatory variable implementation

The aim of this section is to describe the modelling methodologies used for representing mobility tools holding, how socio-economic variables are selected for the models and how to account for specific characteristics of a constrained trip: the home-work trip. In order to set up the modelling implementation in this chapter, a first subsection focuses on the model type theory selection for separately and jointly representing mobility tools holding. It also gives a more detailed description of the socio-economic variables selection process for both model types. A second subsection accounts for the effect of the constrained home-work trip characteristics on the mobility tools holding choice by adding descriptors of this trip as candidate explanatory variables. These involve computing missing modal travel time variables.

5.1.1 Selection of discrete choice models and candidate explanatory variables

5.1.1.1 Models selection

To model the mobility tools holding choice, it is first necessary to define what kind of models are implemented. The models must account for the discreteness of the phenomenon studied and well represent the alternatives available for each choice setting, sometimes involving large choice sets in the portfolio choice case. The traditional candidate models for representing such a phenomenon are from the probit and logit families. Even though other model types are available, both of these are the most diffused in the literature and their interpreting is supported by a lot of studies. Historically, the logit family is very spread out in the transport field of research and provides closed form expressions diminishing model convergence issues – especially when dealing with a high number of alternatives – while its main drawback is the IIA property described in chapter 2 as opposed to the probit family, even though both results generally are close.

Within the logit family, several models exist. The current choice setting is to represent mobility tools holding. The last chapters have shown that this topic is complex because it involves a multiple holding of several mobility tools at the same time. The first models dealing with mobility tools holding only represented one mobility tool – in general, the car – while the last ones represent several mobility tools with portfolio holding models. For gradually addressing the mobility tools holding modelling challenge, this chapter first deals with separate mobility tools holding before representing multiple mobility tools holding. So these first models are replicated for each mobility tools and have a simple binary choice set: either an individual holds the modelled mobility tool or not. This binary choice for the logit family immediately refers to the binary logit model. The formula for the binary logit model with socio-economic explanatory variables is given by Equation 5.1.1, depending on the systematic utility $V(\mathbf{X})$ of the individual's characteristics vector $\mathbf{X}$. $p(\mathbf{X})$ is the probability of choosing one of the two alternatives depending on $\mathbf{X}$. This utility function is detailed in Equation 5.1.2, with ASC referring to the Alternative Specific Variable, $s-e$ referring to the socio-economic variables included in the model, and SE being one of these variables. $\mathbf{X}_{SE}$ is the value of the socio-economic variable SE taken in the vector of and individual's characteristics, and β_{SE} is the vector of the model parameters to determine.

$$p(\mathbf{X}) = \frac{exp(V(\mathbf{X}))}{1 + exp(V(\mathbf{X}))} \tag{5.1.1}$$

$$V(\mathbf{X}) = ASC + \sum_{s-e} \beta_{SE} * \mathbf{X}_{SE} \tag{5.1.2}$$

For the second joint model category involving multiple holding representing, several models are possible within the logit family with different associated choice structures converted into error correlations. This portfolio approach is complex and in order to set the basis for mobility tools holding modelling, a simple logit model is estimated: the multinomial logit, on the choice set of mobility tools portfolios. The formula for the multinomial logit model with socio-economic explanatory variables is given by Equation 5.1.3, depending on the systematic utility of the alternative m, $V_m(\mathbf{X})$ of the individual's characteristics vector $\mathbf{X}$. This utility function is detailed in Equation 5.1.4, with ASC_m referring to the Alternative Specific Variable associated with the alternative m, $s-e$ referring to the socio-economic variables included in the model, and SE being one of these variables. $\mathbf{X}_{SE}$ is the value of the socio-economic variable SE taken in the individual's characteristics vector, and $\beta_{m,SE}$ is the vector of the models parameters for the alternative m. The ASC must be set to 0 for the selected reference alternative, such as all of its related socio-economic parameters, which is the null portfolio for each of the multinomial models implemented.

$$p_m(\mathbf{X}) = \frac{exp(V_p(\mathbf{X}))}{\sum_{CS} exp(V_m(\mathbf{X}))} \tag{5.1.3}$$

$$V_m(\mathbf{X}) = ASC_m + \sum_{s-e} \beta_{m,SE} * \mathbf{X}_{SE} \tag{5.1.4}$$

The multinomial logit can be considered as a generalization of the binomial logit with more than two alternatives. The interpreting of these formula is not complicated: the systematic utility term represents the utility that an individual gets from choosing alternative m. Positive $\beta_{m,SE}$ parameters mean that the higher the associated $\mathbf{X}_{SE}$ is, the higher the utility, so the socio-economic variable favors the choice of the alternative m. The reverse interpreting stands for negative parameter values. Generally, variables such as income are associated with positive parameters as they increase the likeliness of holding goods, while cost variables are associated with negative parameters. The ASC_m term is a constant term of the utility showing the utility granted by the alternative m when all of the socio-economic variables are null. It also standardizes the utility formulation to catch up with the observed market shares. Combined with the error term, the ASC also captures all of the variables non-included in the model. For the present case, it would be expected that all of the ASCs are positive because every portfolio is supposed to grant more utility than the null portfolio. But that may not be the case depending on the reference of the socio-economic variables, and because they also carry the cost of the portfolio not included in the socio-economic variables.

When dealing with the parameters of several alternatives – such as for the multinomial logit and with portfolios – the parameter values must be considered altogether. Indeed, there effect on the utility of the portfolio is important, but it must be understood in comparison with the utility of other portfolios. If income parameters are positive for every portfolio, the ones with the higher value should be identified because it means that income has a higher effect for the associated portfolios than for the others. The interpreting must be carefully made to avoid wrong or incomplete conclusions and to get an overview of the phenomenon.

The multinomial models still face a main issue: when considering seven mobility tools, the number of possible portfolios goes up to $2^7 = 128$. Thanks to the parking space indicator measurement through car holding only, this number is reduced to 64 for the present study, but that still remains a lot of alternatives to deal with. The choice set must be reduced to enable understanding the results. Three restricted choice set are studied in turn: the "Top 3" choice set, the "Traditional" and the "Full" choice sets. All of these restricted choice sets aim on representing the most spread mobility tools portfolio to be statistically representative. The

"Top 3" portfolios combine the 3 most spread mobility tools namely the driving license, the car and the PT pass. Choosing these three mobility tools combination enables getting well represented portfolios with high holding rates for each. The second "Traditional" portfolios choice set combines the most studied mobility tools in the literature namely the car, the PT pass and the bike. This enables to compare the results with other studies. The last "Full" choice set aims on being representative of a high share of the population and all of the mobility tools by including the most spread portfolios in the population and the most spread portfolios by mobility tool. It is based on the statement of the previous chapter that a set of 12 portfolios was enough to describe most of the mobility tools and most of the sub-population. These 12 portfolios are described in the third section of this chapter, before the model results.

When comparing the models associated with the different restricted choice set, it is important to observe that some portfolios have the same name but are still different. For instance, the null portfolio is made of the population not holding a driving license, a car or a PT pass for the "Top 3" choice set, while it is made of the population not holding a car, a PT pass or a bike for the "Traditional" choice set. The model results must be understood within the choice set frame and interactions of alternatives that the choice sets enable.

The drawback of the IIA property for the multinomial logit is also important to consider. It means that every alternative error term is supposed independent from the others. Conceptually, a car portfolio and a car and PT pass portfolio are difficult to consider independents. But they physically are because the portfolios physically are different, and even though conceptually dependent, this does not mean that the error terms have some dependency too if it is completely captured by the explanatory variables. This IIA property still remains a limit of the models developed in this chapter.

A last limit is the meaning of the choice frame. It is assumed that every individual of the sub-population chooses its mobility tools holding portfolio, while it may not always be the case. For instance, some households holding a car but no driving license have been observed in the data set. This choice does not make sense most of the time, except for individuals collecting cars not for using them, but these would likely hold a driving license too. This situation generally better fits the case of individuals in a household where a previous driving license holder individual lived and left, leaving the individual without driving license with a car. Even though such situation is not resulting from a choice, the model will statistically reproduce this setting. But these cases are generally few in number, and the restricted choice set tend to exclude them from the analysis.

More technically speaking, the separate models are built with the R software and their results are presented using the *stargazer* package[1], while the multinomial portfolio models are built using the *apollo* discrete choice modelling package[2] presented in Hess & Palma (2019). These estimate the model by maximum likelihood estimation and the pseudo R^2 indicator and log likelihood indicators are used to evaluate the calibration quality of the models. After this setting of the model frame, the next subsection introduces the candidate explanatory variable selection that feed the models.

5.1.1.2 Selection of candidate explanatory variables

The aim is now to set up a methodology to investigate the effect of the socio-economic variables appearing in the EGT 2010 data set, to determine the ones with the most influence on the mobility tools holding choice. The explanatory variables of the separate choice models are first selected before using another selection process for the multinomial logit models.

Several variable types are considered in this selection step. Category variables must be distinguished from standard variables because category variables are dispatched among a set of binary sub-variables assessing whether the individual belongs to the category value described by the sub-variable, with an omitted reference value. For instance, the IAU commune type category variable is dispatched among several variable category dummies from In-Agglomeration Dense to Rural, each with a 0 or 1 value indicating a 1 when the individual lives in this commune type, the agglomeration centre being the reference value. An individual living in the agglomeration centre will then have every IAU commune type dummy sub-variable with a 0 value as he belongs to the reference value and does not belong to any of the dummy variable values. For the other variables with integer values, simple mathematical transformations are tested: the log transformation to study threshold effects and the square transformation to study parabolic effects. Both are systematically tested along the untransformed variable. In order to avoid issues with the log transformation, a 1 is previously added to the untransformed variable when it can take a null value, which would not yield finite log values. The tested variables for the separate models are presented in Table 5.1.

[1]https://CRAN.R-project.org/package=stargazer
[2]http://www.apollochoicemodelling.com/

Tested variables list
Household location commune
log(Household location commune)
Household location commune^2
Household location commune category
Housing type category
Housing surface
log(Housing surface + 1)
Housing surface^2
Income group
log(Income group + 1)
Income group^2
Age
log(Age + 1)
Age^2
Woman category
Mobility disabled category
Education level
log(Education level + 1)
Education level^2
Socio-professional category
Occupation category
Trip number
log(Trip number + 1)
Trip number^2

Table 5.1 – List of candidate variables for marginal model estimation

After the description of candidate explanatory variables, a process to get the most important variables for the mobility tools holding phenomenon remains to define. The goal is to get a process to run for the 7 separate mobility tool models and to test on the 25 variables. To compare all of the mobility tools, it has been decided to select the three most relevant variables to describe each mobility tool holding. As the number of explanatory variables is set, the log likelihood can be used here to determine the most relevant variables. A "for" loop process has been designed in R to select the combination of three variables, as defined in Table 5.1, that maximizes the model log likelihood. This process is not perfect to determine the best models because the log likelihood is not the only model efficiency indicator to account for. But it remains a practical choice easy to implement and not too much time consuming when dealing with a several models altogether.

Even though this process enables to quickly get the most important variables for each separate mobility tool model, it does not directly give information for the potential explanatory variables for the joint mobility tools holding model. This process cannot be replicated on the joint models because it would be a lot more time consuming with 7 times more parameters to test. It has been decided to keep all of the explanatory variables available for these joint models because optimizing each of these would be very time consuming too, and because models with a lot of variable can still be interpreted. The only selections are on linear variables against a category variable when it was also available, and on log against square non-linear transforms for naturally linear variables to test potential non-linear effects on mobility tools holding.

After setting up the model analysis frame, it still remains to account for one important phenomenon effect on mobility tools holding: the effect of constrained trips characteristics on the mobility tools holding choice.

5.1.2 Inclusion of constrained trips characteristics

The initial setting only focuses on the available socio-economic variables. But the mobility tools holding choice is not only a step before a travel mode choice within a classical four step model framework, or the result of socio-economic characteristics only. Indeed, the relationship between mobility tools holding and travel mode choice is much more complex and it is not valid to state that only one constrains the other. While addressing the issue of occasional or unconstrained trips is still very difficult, it is very likely that constrained trips are determinants of mobility tools portfolios. The travel mode choice associated with having to travel on a daily basis on an origin-destination pair is probably more a basis for the portfolio choice than the reverse is. In order to account for this element of the mobility tools portfolios holding choice, this subsection focuses on integrating regular home-work trip characteristics in the models. Home-work trip is indeed the most traditional and studied constrained trip, and also the easiest one to identify. This also fits the sub-population which has a high share of active individuals.

But the only trip duration or cost data available on the home-work trip in the EGT 2010 is its crow-fly length which does not mean much in itself because individuals are usually expected to be more sensitive to price and travel time than trip length. This subsection aims on building new home-work trip characteristics to add in mobility tools portfolios holding models to make them more sensitive to these structural constrained trips. It describes how travel times for car, public transport, motorcycle, bike and walk modes have been computed, before displaying a quick analysis of travel times most relevant effects of the computed travel times on some key mobility tools holding.

These variables are calculated using Transcad on the Paris region with network and calibration data from the MODUS 2008 model developed by DRIEA IF, a French State organism managing main road infrastructures. The decision to use imperfect calculated travel times and not observed one is threefold. First observed travel times are not completely reliable because they depend on dynamic traffic conditions and because reported travel times are very often rounded up to 5 or 10 minutes steps. Second, the goal when generating these variables is to compare the different mode choice characteristics, and unobserved mode options characteristics are not available by definition. With regard to the first two elements, it would have been possible to use observed data when available and calculated ones for unobserved choices, or to use different models more adapted to the public transport or road transport modelling. The issue with the latter approach is that it mixes different biases: observation biases for observed variables and model biases for calculated variables. In order to get comparable variables with the same biases, it has been decided to compute every origin-destination travel time with the MODUS model.

By definition, this process implies reducing the study population to the active population making home-work trips. The EGT 2010 has some information on some workplace characteristics such as its type, its location, whether the individual has a unique workplace or not, whether parking spaces are available or not. These test variables are added to the previous socio-economic variables and are included in the selection process of candidate explanatory variables, just as socio-economic variables. They are summed up in Table 5.2.

Additional tested variables list
Workplace type category
Workplace unicity
Workplace location commune type
log(Workplace location commune type + 1)
Workplace location commune type^2
Workplace location commune category variable
Workplace car parking available
Workplace bike parking available
Home-work walk trip travel time
(Delta travel times depending on the mobility tool)

Table 5.2 – List of additional candidate variables for marginal model estimation

The last variable refers to the observed differences of computed travel times and depends on the mobility tool. For mobility tools directly associated with a travel mode such as car or PT pass, this refers to the set of differences between the travel time of this associated mode for the home-work trip, and the other modes: walk, bike, PT, motorcycle and car. This choice to focus on travel time differences is made to emphasize on the mode and associated mobility tool competitive advantage or disadvantages over other modes. While accounting individually for the travel time of each mode would have been a possibility, these would be more difficult to understand. These travel times are not selected as test variables but always included to see which ones seem to be the most relevant to include in portfolio models. The driving license and parking space mobility tools do not have these explanatory variables because they are not directly related to the home-work trip mode choice, but rather related through another mobility tool: the car for both cases.

The main challenge for modelling travel times is the difference between the MODUS model zoning system based on 1,289 zones with a $9.8km^2$ average surface and the EGT 2010 zoning system based on 1,489,347 zones with a $0.01km^2$ surface each. In order to benefit from the very accurate zoning system of EGT observations, a process is designed to disaggregate the initial Modus zoning into the more accurate EGT 2010 zoning. The following paragraphs first define the network terminology and highlight the computation process with concerns regarding issues of data set size. Second, they describe how the transport networks are built and how the free flow and congested travel times are calculated for each network link. Third, they explain how the networks is disconnected from its original MODUS zoning to be connected to the EGT 2010 zoning before concluding on results of this computation process and analysing the effects of some computed travel times on mobility tools holding.

5.1.2.1 Process and network terminology

To avoid misunderstandings, the vocabulary used for the description of the travel times calculation process must be set. Two main data categories are involved in this process: *geographical data* and *network data*:

The *geographical data* describes the geographical ***zones***. In order to connect the zones to a network layer, ***centroid*** points where the zone data is aggregated are built. An illustration of these objects is displayed in Figure 5.1. The MODUS zoning is built on 1,289 zones. Their centroids have been manually set by DRIEA IF transport planners to be relevantly located at the barycentre of the employment and residential population of the MODUS zone. This qualitative step is important to avoid getting centroids in the zone centre which could be in the middle of a park or forest where nobody lives nor travels. The EGT 2010 is more disaggregated with its 1,489,347 100m side squares. As a result, taking centroids at the zone centres is relevant with a maximum $\frac{\sqrt{2}}{2}.100 = 71$m error.

The *network data* describes the network characteristics. The network is built as a set of ***links*** and ***nodes*** with each link connecting two nodes together and one node being connected to at least one link. In order to connect the geographical data to the network data, ***connectors*** must be implemented to link network nodes with zone centroids. Connectors are additional links and centroids are additional nodes built in the link data set and in the node data set respectively. The MODUS 2008 road network has 39,420 links connecting 19,901 nodes.

Transit networks require a more detailed approach to account for transit vehicles frequency effects and the additional cost of riding different transit lines and vehicles during the same trip. Instead of a simple set of links, there is an additional ***transit lines layer*** and an additional ***transit missions layer***. These layers are complements of the link layer specifying whether stops belong to the same transit line or not for the line layer, and then whether stops belong to the same vehicle mission or not for the mission layer. Vehicle missions gather the set of vehicle reaching the same stops on the same transit line. An example of missions is the set of omnibus train and another set of express train skipping some stops on a transit line. The MODUS 2008 transit network has 58,482 links connecting 16,177 nodes.

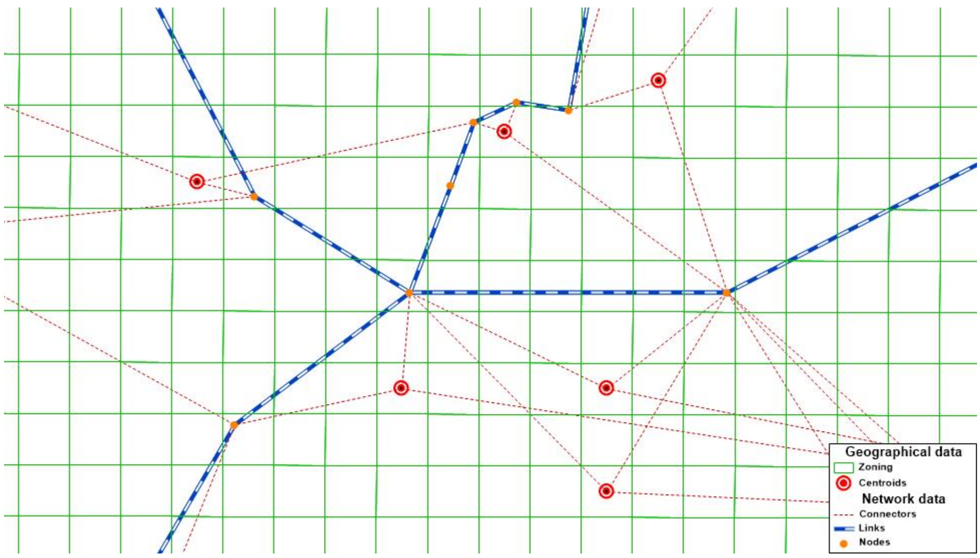


Figure 5.1 – Screenshot illustrating road and network data objects in Transcad

In order to compute the travel times for each mode at the EGT 2010 level, a standard process needs to be drawn:

1. Open the network and geographic files at the MODUS 2008 zoning scale and assign free-flow travel times to the links,
2. Load the network with a peak hour Origin-Destination matrix and run an assignment procedure to get loaded network travel times for the links,
3. Disconnect the network from the MODUS 2008 zoning data,
4. Open the EGT 2010 geographic files,
5. Connect the EGT 2010 geographic files to the MODUS 2008 network files,
6. Compute EGT 2010 Origin-Destination travel time matrices for free-flow and loaded links,
7. Extract the data and assign it to the EGT 2010 observations.

This process does not seem much complicated but an issue encountered is the size of the EGT 2010 data set. Computing the Origin-Destination travel times for each of the 1,489,347 EGT 2010 centroids would yield more than 2 billions Origin-Destination travel times. Even though Transcad might be able to deal with such figures, the calculation time would still be very important and the data would not easily be exported to a statistical software such as R to run analyses.

In order to face the data set size issue, a first step is to focus on specific Origin-Destination couples. This whole process aims on building home-work or home-studies related travel times for the population of the individuals living in one individual households. The 35,175 individual observations become 2,579 specific individual cases. Connecting the residential location and the work/studies location for each of these specific individual cases yields 4,534 different EGT 2010 zones with about 20.5 million Origin-Destination pairs. This number is reduced to 5.5 million pairs by accounting whether the EGT 2010 zones appear only as origins or destinations, not connecting two destination-only or two origin-only zones.

5.1.2.2 Transport networks construction and loading

This paragraph deals with the first two steps of the process. It depends on the network type used and is separated for each different road, public transport or walking and biking networks.

Road Network The road network files used are the MODUS 2008 ones. They are based on the MODUS zoning and the link and node files already incorporate description of the centroids and connectors to the MODUS zoning. They are adapted to the 2008 year while the EGT data with which it will be compared is from 2010, which is not an issue because the infrastructure was already well developed and no major road infrastructures were implemented during this period. For each link, its characteristics were initially given. Free-flow travel times have been computed in minutes by dividing the link length by the link free-flow speed. Alpha and Beta coefficients to evaluate congestion conditions were also given.

The Transcad network file was built on that data. An Origin-Destination flow Matrix for the PM peak hour in passenger car equivalents set for the 2009 year has been used to load the network. A static assignment is computed by using the "N Conjugate UE" Transcad package. This package implements a Frank-Wolfe algorithm to reach minimal travel time User-Equilibriums and accounting for congestion patterns with the Bureau of Public Roads function:
$TravelTime = FreeFlowTravelTime.(1 + \alpha.(\frac{Flow}{Capacity})^{\beta})$
α and β are parameters characterizing the congestion patterns of the road link. This static assignment enables getting congested travel times for the network links. These congested travel times are stored in a new link variable.

Motorcycle congested links have also been implemented to account for lower congestion disturbances for this mode. The new link travel time calculation is based on Lee et al. (2012). This article states that on average, the urban speed during the peak hour in London is at 25km/h for cars and at 36km/h for motorcycles. After a quick literature review, peak hour versus free flow speed values for motorcycles have not been often observed, so these have been used for the current study. This choice is also consistent because Paris and London have close socio-economic, and cultural profiles and geographic proximity. The congested travel times for motorcycles are set to:
$max(FreeFlowTravelTime, CarCongestedTravelTime.\frac{25}{36})$

Public Transit Network The public transit network files used are also the MODUS 2008 ones. As explained in the first section, the network files must be expanded with a Route System file compiling data at the transit line level. This Route system is completed with more accurate data describing the mission attributes issued from a Mission Attributes file. In order to specify transfer between modes conditions, a Mode Table and a Mode-Mode Transfer Table files are added to build the final transit network. All of these files are issued from the MODUS 2008 model.

The assignment step from the MODUS 2008 model does not account for congestion effects so there is no loading step: the transit network is directly disconnected from

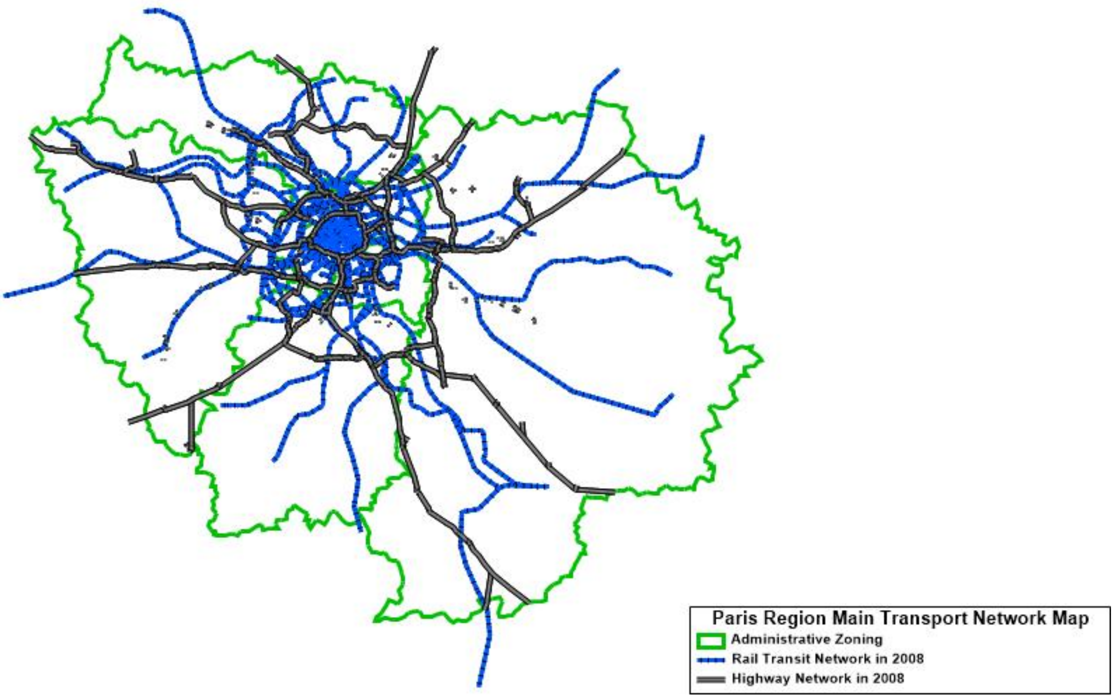


Figure 5.2 – Paris region main transport networks map

the MODUS 2008 zoning. It comes from the lack of boarding time congestion effects representation delaying transit vehicles scheduled missions. The assignment procedure used for computing Origin-Destination time matrix is the Pathfinder Transcad procedure enabling transfers between different missions.

Walking and Biking Networks There were no existing walking and biking networks in MODUS 2008, and no Paris region transport model represents these either to the author's knowledge. This fact comes from the lack of studies on pedestrian crowding in the streets, the under representativeness of cycling in the modal share and the original model theorization around the car and public transit use only. In order to still account for biking and walking mode characteristics, flying links not considering the Paris region topology and geography are generated. Geographical effects are roughly considered by assigning different link speed, as described in the third section. Even though inaccurate, this approach makes the best with the available data and development time constraints.

5.1.2.3 Connection between the network and the EGT 2010 zoning

The process of disconnecting the network files from the preset MODUS zoning and the process of connecting the unconnected network to the EGT 2010 zoning must then be addressed. This is made in three steps:

1. Delete the MODUS centroids and connectors,
2. Create new connectors between EGT 2010 centroids and network nodes,
3. Assign travel times to the new connectors.

The first step is easy to implement and one should just be careful to drop the previous networks encompassing previous connectors and centroids before deleting these.

The second step is not so straightforward. Indeed, a first approach would have been to simply build one connector connecting each centroid to a network node. But this approach is flawed: if a centroid is very close to a node reached by a link with a very high travel time value, while there is a second node a few meters away reached by a second link going to the same destination as the first link but with a much lower travel time value, then the first connector does not yield an optimal solution and travellers would probably choose the second connector. In order to take into account this possibility, several connectors are drawn for each centroid. For the road network, 3 connectors are drawn for each centroid while 5 connectors are drawn for each centroid for the transit network. These figures are qualitatively chosen considering the computation time for this procedure and the necessity to get more connectors to the transit network because it is less spread and displays less inter-connectivity possibilities.

This step may first seem natural, but it is a very theoretical approach not considering geographical constraints. The small roads networks are not represented in the MODUS model and it is not possible to know whether the connectors created have a corresponding real path are not. The worst case that can be faced is the existence of a physical barrier such as a stream, a field a forest or the lack of roads between a centroid and a close node. Unfortunately, there is no way to simply deal with these issues with the available data and without a time-consuming manual calibration, and these limits must be considered when analysing the results. Hopefully, the goal of this travel time calculation is to compare modal travel times and one can hope that these biases most of the time cancel out because this procedure is conducted for each travel time calculation. This bias belongs to the Modifiable Areal Unit Problem (MAUP) better described and addressed in Manout (2019).

The third step assigning a travel time value to each connector is important because otherwise Transcad considers that the travel time value of connectors is null. For each connector the length is automatically determined: the travel time assignment depends on the speed assigned to each connector. In order to account for average speed variations, it has been decided to set different average speeds linked to the metropolitan area characteristics. A good overall indicator is to differentiate by "Couronne": The first modality is the Paris city i.e. the agglomeration centre, the second modality is the "Petit Couronne" encompassing the first administrative departments ring, and the third modality is the "Grande Couronne" encompassing the last departments in the Paris region. These three modalities roughly mark off down-town environments with low driving speeds and high walkability, suburban environments with average driving speeds and average walkability, and rural environments with high driving speeds and low walkability. The chosen speeds are based on other Paris region models speeds, EGT 2010 processing and qualitative estimations. These characteristics are summed up in Table 5.3.

Car and Motorcycle			Public Transit	Biking	Walking
Paris city	*Petite Couronne*	*Grande Couronne*			
15 km/h	30 km/h	60 km/h	5 km/h	15 km/h	5 km/h

Table 5.3 – Connector speeds table

The figures displayed in Table 5.3 are averaged and rounded up at 5km/h because they are not accurate. Indeed, they show connector travel speeds which are not equivalent to overall travel speeds. The public transit connectors speed is low because it is considered to be made walking.

5.1.2.4 Computed home-work travel times effects on mobility tools holding

Figure 5.3 presents the result of the mobility tools holding analysis depending on the computed walk travel times for the home-work trip. As explained earlier, the walk travel times are flying distances made at a 5km/h speed, so they are linearly related to this home-work trip flying distance. These suggest very singular patterns for car and PT pass holdings. Indeed, it seems that PT pass holding quickly grows from 0 to 45 minutes trips, to about 66%, staying at this value until about a 100 minutes trips before reaching another threshold at about 59% holding rates. On the car holding side, it stays at a threshold at 43% until a 100 minutes walk trips, before increasing and reaching a threshold at 79% above 150 minutes. These observations are tested with fitted curve matching the observed data with R^2s above 0.9. This figure enables to identify three main trip walk travel times effects: a *walkability and bikability range* for home-work walk trips duration under 45 minutes where PT pass and car holding are not very high, where cycling and walking are competitive modes, an intermediate *public transit competitive range* for home-work walk trips between 45 minutes and 100 minutes, and a final *car competitive range* for a home-work walk trip duration above 100 minutes.

In addition to this home-work trip walk travel time or distance effect, the competitiveness of each mobility tool relies on the competitiveness of the associated travel mode. This competitiveness appears when comparing the trip duration using a mode with the trip duration using other modes, so travel time differences have been computed and investigated. Two main effects have been observed: the effect of the difference between PT and congested car travel times and the effect of the difference between PT and bike travel times.

The difference between PT and car travel times is illustrated in Figure 5.4. The more negative the difference is, the more the car mode is competitive against the PT mode, and the more positive it is, the more competitive the PT is over the car mode. The car is almost always quicker than the PT mode, but most of the time there is a difference between these travel times under 10 minutes. The graph shows a decreasing trend for car holding fitted with a reversed logit cumulative curve, and an opposite increasing PT pass holding fitted with another logit cumulative curve. The curve fit the data with R^2s around 0.9 so they are very close. The trend change point where the PT pass is more held than the car appears for a difference at about -15minutes, indicating the car travel times is 15 minutes lower than the PT travel time for the home-work trip.

Another less significant effect is described in Figure 5.5 illustrating the difference between PT travel time and bike travel time. While this graph is more balanced with many negative and positive values, the PT pass holding share seems to stay at a threshold before decreasing at a 0 minute difference before a quick decrease. This may mean that when the PT travel time overcomes the bike travel times then the home-work trip enters within the bikability range and PT pass holding drops. On the other side, the bike and bike sharing holding do not highlight meaningful trends.

This subsection has implemented new travel time variables and shown that these give a new insight on the effect of home-work trip travel times on mobility tools holding. Now that the modelling methodology is set, the next section focuses on the separate models.

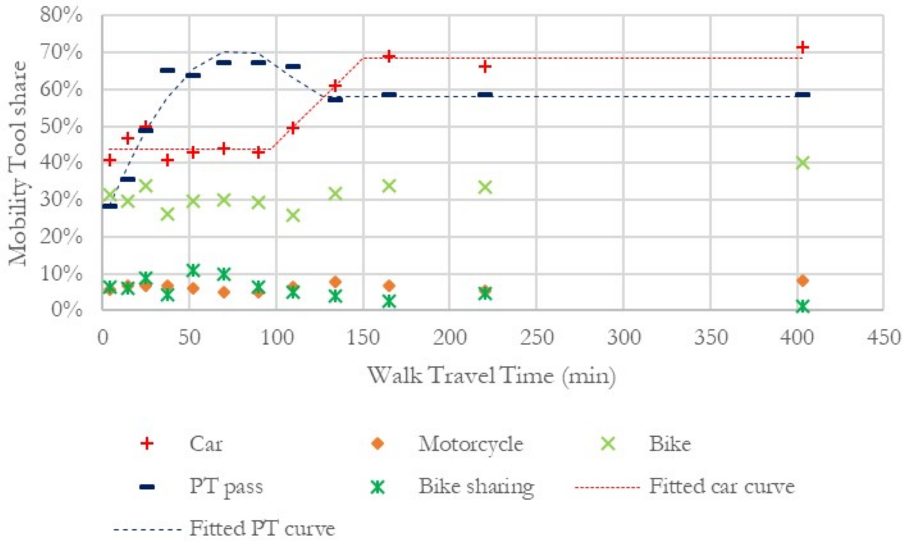


Figure 5.3 – Mobility tools holding depending on home-work walk travel time

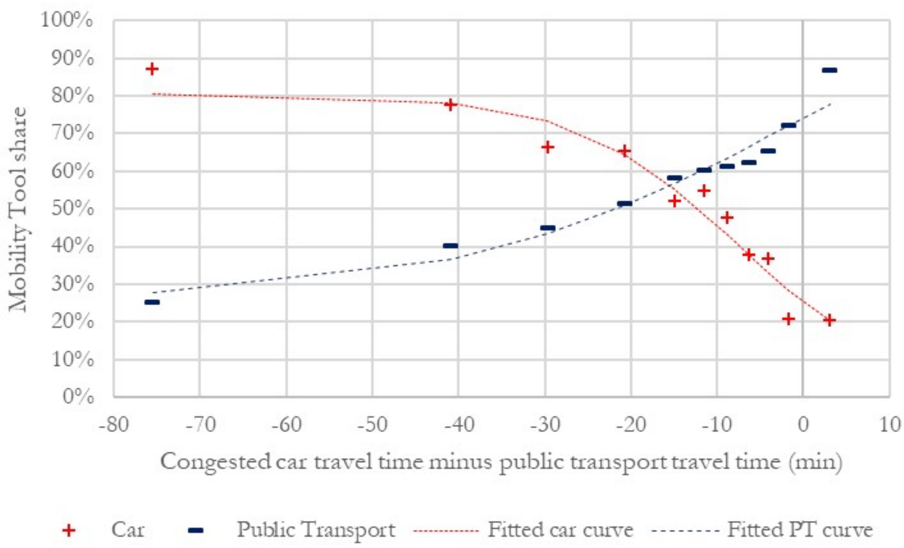


Figure 5.4 – Mobility tools holding depending on the differences between PT and congested car travel times for the home-work trip

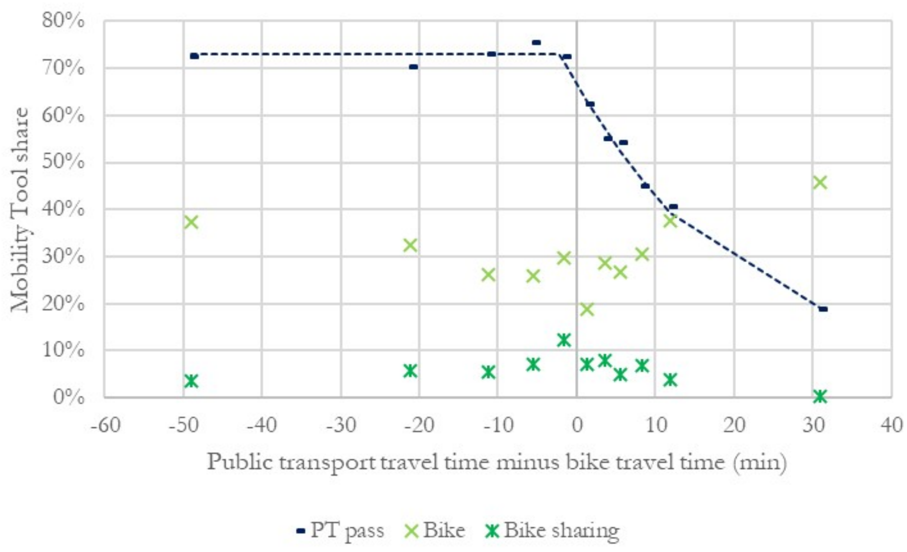


Figure 5.5 – Mobility tools holding depending on the differences between PT and bike travel times for the home-work trip

5.2 Separate Holding Models

Now that the modelling frame is set, that the model type is selected and that the candidate variables are described, the models can be implemented. The separate models for the whole sub-population of individuals living in households with only one individual of the Paris region can be estimated with the EGT 2010 data set in the first subsection. This makes a total of 5,036 observations, enabling to run robust statistical analyses. The second subsection adds the home-work constrained trip characteristics to the analysis and presents separate models for the active sub-population made of 2,796 individuals[3]. The model results are fully displayed and summarized to increase the readability of the overall mobility tools holding phenomenon. A last third subsection provides comparative analyses of the results considering other modelling options.

5.2.1 Separate holding models for the whole sub-population

The results of each of the separate mobility tool holding models – which can be considered as marginal models of the more complex multinomial mobility tools holding model – are presented in Table 5.4, Table 5.5, Table 5.6, Table 5.7, Table 5.8, Table 5.9, and Table 5.10. Individual and private vehicle mobility tool models are first presented before mobility service subscription models. This subsection first deals with each model separately before analysing the models altogether.

[3]This number of observations is higher than the 2,579 observations in 5.1.2, because it includes all of the active sub-population, not only the one with individuals who provided enough home-work trip characteristics to compute the corresponding travel time.

Driving license holding model for the whole sub-population

	Dependent variable (standard error):
	Driving License holding
Intercept	−0.519*** (0.136)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	0.022 (0.104)
In-Agglomeration Urbanized	0.280** (0.118)
In-Agglomeration Other	0.623*** (0.192)
Out-Agglomeration Main	0.210 (0.174)
Out-Agglomeration Other	1.309*** (0.333)
Rural	1.808*** (0.403)
Squared income group variable	
Income^2	0.046*** (0.004)
Squared education level variable	
Education level	0.194*** (0.018)
Observations	5,036
Null Log Likelihood	−2,308.294
Log Likelihood	−2,009.718
McFadden's pseudo R^2	0.129
AIC	4,037.437
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.4 – Marginal model of driving license holding for the sub-population

First, the three main variables describing driving license holding for the whole sub-population identified are the household location commune category variable, the squared income group variables and the squared education level variable. Overall, the R^2 is not very high at 0.129, suggesting that the model is not very efficient for explaining the data set. The intercept is significantly negative, so the reference population – the individuals living in the city centre in the lowest income and education groups – are less likely to hold a driving license than on average. The household location commune variable parameters are consistent with a gradually higher utility for individuals in household further away from the city centre. The rural household category variable even reaches more than three times the intercept value, witnessing a strong geographical impact. Even though the parameter values are low for the squared income group and squared education level variables, their low standard deviation make them significant. So the higher the income and education level, the higher the likelihood of holding a driving license. The non-linearity of these two variables means here that their effect on driving license holding is stronger and increasing with higher levels than a linear approach.

Car holding model for the whole sub-population

	Dependent variable (standard error):
	Car holding
Intercept	−5.537*** (0.284)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	1.231*** (0.087)
In-Agglomeration Urbanized	1.934*** (0.101)
In-Agglomeration Other	2.088*** (0.154)
Out-Agglomeration Main	1.874*** (0.154)
Out-Agglomeration Other	2.691*** (0.265)
Rural	2.843*** (0.280)
Log-transformed housing surface variable	
log(Housing Surface + 1)	0.876*** (0.072)
Income group variable	
Income	0.279*** (0.017)
Observations	5,036
Null Log Likelihood	−3,457.215
Log Likelihood	−2,812.345
McFadden's pseudo R^2	0.187
AIC	5,642.690
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.5 – Marginal model of car holding for the sub-population

The car holding model also has a low R^2, but with a much higher negative value for the intercept parameter. This means that the reference population – the individuals with their household in the city centre, with very low housing surface and from the lowest income group – is a lot more unlikely to hold a car. It makes sense because the car has a high maintenance cost that is difficult to afford for low income individuals, even more in the city centre where the parking costs are much higher. The effect of the household location commune type is similar as for driving license holding, with higher chances of holding a car in less urbanized communes, which makes sense because there generally is less modal competition in rural areas. The income is also positively associated with car holding, which is consistent with most of the existing literature on car holding models. It must be noticed that the car effect is linear rather than exponential. Last, the housing surface variable has a decreasing marginal effect on car holding as it is its log-transformed variable that is used in the model. Among individuals with high surface housings, having a larger surface does not imply being much more likely to hold a car than among individuals with low surface housings.

Parking space holding model for the whole sub-population

	Dependent variable (standard error):
	Parking space holding
Intercept	−7.622*** (0.325)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	0.989*** (0.098)
In-Agglomeration Urbanized	1.539*** (0.106)
In-Agglomeration Other	1.649*** (0.149)
Out-Agglomeration Main	1.299*** (0.155)
Out-Agglomeration Other	2.015*** (0.219)
Rural	1.470*** (0.205)
Log-transformed housing surface variable	
log(Housing Surface + 1)	1.254*** (0.079)
Income group variable	
Income	0.248*** (0.016)
Observations	5,036
Null Log Likelihood	−3,303.086
Log Likelihood	−2,751.152
McFadden's pseudo R^2	0.167
AIC	5,520.305
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.6 – Marginal model of parking space holding for the sub-population

When looking at the parking space holding model, it appears that it is almost the same as the car holding model: the same three explanatory variables are included, but with higher positive values for the variables parameters, and a higher negative value for the intercept. So the variations are also quite similar. These higher variation of the utility are associated with a lower holding likelihood than for the car mobility tool, but similar dependencies to the explanatory variables. This makes sense because the parking space variable is only available for car holders, justifying a degree of similarity between both models. Here, it is almost as if the model is replicating car holding rather than the more detailed parking space holding.

Motorcycle holding model for the whole sub-population

At the difference of the previous models, the motorcycle holding model has completely different explanatory variables. Aside its high negative intercept value, it is defined by the housing type, the gender and occupation category variables. Individuals living in collective housings are more likely to hold this mobility tool,

	Dependent variable (standard error):
	Motorcycle holding
Intercept	−4.350*** (1.069)
Housing type category variable(reference: Other)	
Collective Housing	0.195 (1.040)
Individual Housing	1.021 (1.051)
Gender category variable(reference: Man)	
Woman	−1.823*** (0.191)
Occupation category variable(reference: Retired)	
Wull-time Worker	2.023*** (0.285)
Part-time Worker	1.997*** (0.418)
Homemaker	−11.080 (322.145)
Unemployed	1.293*** (0.439)
Student	0.890 (0.580)
Inactive and NA	0.879 (0.771)
Observations	5,036
Null Log Likelihood	−916.192
Log Likelihood	−783.329
McFadden's pseudo R^2	0.145
AIC	1,586.657
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.7 – Marginal model of motorcycle holding for the sub-population

but not in a significant way. Motorcycles are significantly negatively associated with being a woman, making it a gender biased mobility tool. It is a lot favoured by active workers and by unemployed individuals. The first category probably because it has a high mobility need and is confronted with peak hour congestion when motorcycles have traffic avoidance advantages, and the second category probably because it is less financially able to buy a car and uses the motorcycle as an intermediate step to car holding. When considering the results of the analysis from Chapter 4, this is also consistent with the active and physically able age group previously identified.

Bike holding model for the whole sub-population

The bike holding model has a very low R^2, probably because the cost of the bicycle is so small that it may not be held for regular mobility uses, but rather for occasional uses. Its low cost makes it available to almost everyone too, and socio-economic variables are not able to well explain its holding. It has a high negative intercept value, and is highly influenced by the age variable, represented linearly and with a non-linear log component. These suggest a negative parabolic effect:

	Dependent variable (standard error):
	Bike holding
Intercept	−20.348*** (1.618)
Housing Surface variable	
Housing Surface	0.014*** (0.001)
Age variable	
Age	−0.167*** (0.012)
Log-transformed age variable	
log(Age + 1)	6.985*** (0.568)
Observations	5,036
Null Log Likelihood	−3,044.489
Log Likelihood	−2,852.979
McFadden's pseudo R^2	0.063
AIC	5,713.958
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.8 – Marginal model of bike holding for the sub-population

the holding likelihood increases first for low age groups, stabilizes at average age groups before decreasing at high age groups. This is consistent with the physical ability necessary to ride a bike. The housing surface variable is also significant, but with a low parameter value. So individuals in bigger housings are more likely to hold a bike.

PT pass holding model for the whole sub-population

Switching to mobility services models, the PT pass holding model has a low and significant positive parameter value, suggesting high effects from explanatory variables. The reference population – the individuals living in the city centre, with a low housing surface and retired – is more likely to hold a driving license on average. The geographical effect of the household location commune variable is negative, gradual and strong: the further away from the city centre, the lower the changes of holding a PT pass subscription. This is consistent with lower PT services in less urbanized and less dense communes. The housing surface is combined with this first geographical variable, with a negative parameter too. This confirms the high importance of the geographical location and housing on PT pass subscription holding. Last, the socio-professional categories are found to have a strong impact on PT pas holding. Individuals without activity or employed are more likely to hold a PT pass, than retailer which often are independent workers, not benefiting from the mandatory company financial participation to PT pass subscription, or from social programs.

	Dependent variable (standard error):
	PT subscription
Intercept	0.636*** (0.110)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	−0.609*** (0.080)
In-Agglomeration Urbanized	−1.128*** (0.093)
In-Agglomeration Other	−1.380*** (0.148)
Out-Agglomeration Main	−1.741*** (0.165)
Out- Agglomeration Other	−2.564*** (0.341)
Rural	−2.374*** (0.316)
Housing Surface variable	
Housing Surface	−0.012*** (0.001)
Socio-professional category variable(reference: Retired)	
No Activity	1.378*** (0.191)
Employed	0.923*** (0.100)
Blue Collar Worker	0.426*** (0.134)
Intermediate Profession	0.630*** (0.089)
Retailer	−0.989*** (0.325)
Executive	0.648*** (0.090)
Observations	5,036
Null Log Likelihood	−3,425.588
Log Likelihood	−2,982.448
McFadden's pseudo R^2	0.129
AIC	5,992.895
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.9 – Marginal model of PT pass holding for the sub-population

Bike sharing subscription holding model for the whole sub-population

Last, the bike sharing model is similar with the PT pass holding model, but with more specific variable effects. The intercept variable has a high, negative and significant value. The geographical household location variable has a much marked effect and is not gradual: either an individual is in the city centre, or she is out of the core of the agglomeration and it is not likely to hold a bike sharing subscription. It also seems to be a mobility tool targeting educated individuals from medium to high socio-professional categories – the new services adopters – and some individuals without activity, probably for financial motivations.

Cross-analysis of the separate models for the whole sub-population

A summary of these models is displayed in Table 5.11 to help building a general analysis running over the seven models.

	Dependent variable (standard error):
	Bike Sharing subscription
Intercept	−4.707*** (0.421)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	−1.091*** (0.185)
In-Agglomeration Urbanized	−2.758*** (0.463)
In-Agglomeration Other	−2.368*** (0.721)
Out-Agglomeration Main	−16.596 (604.637)
Out-Agglomeration Other	−16.311 (897.858)
Rural	−2.126** (1.014)
Squared education level variable	
Education level^2	0.017*** (0.005)
Socio-professional category variable(reference: Retired)	
No Activity	2.027*** (0.540)
Employed	1.118*** (0.374)
Blue Collar Worker	0.818 (0.650)
Intermediate Profession	1.370*** (0.314)
Retailer	0.804 (0.773)
Executive	1.808*** (0.297)
Observations	5,036
Null Log Likelihood	−726.307
Log Likelihood	−589.244
McFadden's pseudo R^2	0.189
AIC	1,206.488
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.10 – Marginal model of bike sharing subscription for the sub-population

Overall, McFadden's pseudo R^2s indicating the share of the variance explained by the model are not very high between 0.06 and 0.19, but that probably comes from the low number of variables, and from the low share of some mobility tools such as motorcycle and bike sharing subscription holding. The parameters are almost all significant at the 99% threshold. The variable which is the most represented within the seven models is the household location commune category appearing in five models, then the household surface appearing in four models and then the income variables appearing in three models. Clearly, this means that the geographical location is a main descriptor of a mobility tool holding. The housing surface is a related variable mixing geographical and economical information as high surfaces are associated with housing far from the city centre or expensive, and which can also be interpreted as a housing bike parking availability. The income effects mostly appear in the driving license holding, car holding and parking space hold-

Mobility tool modelled	McFadden's Pseudo R2	AIC	Variables
Driving License	0.13	4,037	Household location commune category Squared income group Education level
Car	0.19	5,643	Household location commune category Log-transformed household surface Income group
Parking space	0.17	5,520	Household location commune category Log-transformed housing surface Income group
Motorcycle	0.15	1,587	Housing type category Gender category Occupation category
Bike	0.06	5,036	Housing surface Log-transformed age Age
PT Pass	0.13	5,993	Household location commune category Housing Surface Socio-rofessional category
Bike Sharing	0.19	1,206	Household location commune category Squared education level Socio-Professional category

Table 5.11 – Comparison of the results of the marginal models for the sub-population

ing models, suggesting that it is a better explanatory variable for these than for mobility services and other not car related private vehicles. The socio-professional category is not as much important as it was expected and mostly appears in mobility services subscription models.

Looking at Table 5.11 with the previous mobility service structure ranking also brings information on the phenomenon. Indeed, it appears that the car equipments are mostly related to geographical and income variables, while mobility services subscription is more related to socio-professional, education and geographical variables. Motorcycle holding and Bike holdings are much different as they do not have the household location commune category in the top 3 explanatory variables, but rather fixed individual characteristics such as gender for motorcycle holding and age for bike holding. Yet, there still is a geographical proxy variable in these last models because the housing type is strongly related to the geographical location commune type, but with a much less detailed category scale.

To sum up the results of the parameter analysis for the previous models: for the driving license holding model, the further away from the city centre the household is, the richer and the more educated it is, the higher the likelihood of holding a driving license. The car holding and the parking space holding models are almost identical, with increased likelihood of holding these mobility tools with higher income, with living in low-urbanized communes and with log-transformed household surface. This log-transformation illustrates a threshold effect on a variable mixing the effects of the two others. The motorcycle model is not compatible with an income or direct household effect as told in the previous paragraph. Even though not significant, it seems that living in an individual housing favours motorcycle holding, and that being a woman decreases the motorcycle holding likelihood. It is also associated with worker and unemployed individuals as opposed to retired and home-maker individuals. For the bike holding, a large house surface corresponds to higher holding rates, while the effect of age is difficult to understand because there is a mix of the age variable with the log-transformed age variable. But this mix seems to indicate a higher likelihood for the middle-aged individuals as opposed to the older and younger adult population. The bike and motorcycle models target very close population characteristics as the worker and unemployed individuals can most of the time fit in this middle-aged population. PT pass holding is deteriorated with less urbanized household location communes and higher housing surface, while being associated with no activity and working populations. The bike sharing models is similar with higher household location commune and socio-professional category parameters suggesting stronger effects.

The results of this first modelling step confirm the analyses in chapter 4 with very similar patterns for car equipments models, for the motorcycle and bike models and for the mobility services models. The geographical variable is the main explanatory variable that appears in almost every model, followed by income variables for the car equipments mobility tools models, and socio-professional category for the mobility services models, and by age-related variable for the motorcycle and bike model.

5.2.2 Separate holding models for the active sub-population

The results of the optimization process to find the most significant socio-economics and home-work trip characteristics on separate mobility tools are displayed in Table 5.12, Table 5.13, Table 5.14, Table 5.15, Table 5.16, Table 5.17, Table 5.18. Like in the previous subsection, the models are separately analysed before conducting a more general analysis.

Driving license holding model for the active sub-population

First, the driving license holding model for the active sub-population is less modified than the others by adding home-work trip characteristics because no

	Dependent variable (standard error):
	Driving License holding
Intercept	−2.267*** (0.424)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	0.068 (0.146)
In-Agglomeration Urbanized	0.345** (0.165)
In-Agglomeration Other	1.124*** (0.301)
Out-Agglomeration Main	0.653** (0.277)
Out-Agglomeration Other	15.275 (325.268)
Rural	2.012*** (0.736)
Squared income group variable	
Income^2	0.046*** (0.005)
Education level variable	
Education level	1.424*** (0.197)
Observations	2,796
Null Log Likelihood	−1,167.224
Log Likelihood	−1,022.633
McFadden's pseudo R^2	0.124
AIC	2,063.3
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.12 – Marginal model of driving license holding for the active sub-population

travel time is directly associated to it. The R^2 is low and the intercept value is significantly negative, so the reference population – individuals living in the city centre with low income and education level – is not well equipped with it. The variables impacting driving license holding are the household location commune type, the squared income group and the education level. The effect of the household location commune is not steady and not always significant. But all of the parameters are positive and being out of the agglomeration seems to favour its holding. The high parameter and standard error value for the Out-Agglomeration dummy variable is probably caused by a lack of observed individuals with a household in this commune type. The effect of the income variable is increasingly stronger with higher income groups as it is its square transformation that is the most significant, favouring driving license holding even more for higher income groups. The education level variable has a strong, significant and positive parameter value inducing higher holding rates for the educated population. Aside these socio-economic explanatory variables, no home-work trip variables are included in this model, suggesting that these characteristics of constrained trips do not impact much driving license holding.

Car holding model for the active sub-population

	Dependent variable (standard error):
	Car holding
Intercept	−6.485*** (0.502)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	1.302*** (0.140)
In-Agglomeration Urbanized	1.837*** (0.174)
In-Agglomeration Other	1.964*** (0.263)
Out-Agglomeration Main	1.477*** (0.327)
Out-Agglomeration Other	16.346 (347.032)
Rural	2.389*** (0.820)
Log-transformed housing surface variable	
log(Housing Surface + 1)	1.081*** (0.127)
Income group variable	
Income	0.260*** (0.028)
Travel time differences variable	
Walk - Car	−0.009 (0.012)
Bike - Car	0.028 (0.040)
PT - Car	0.028*** (0.005)
Motorcycle - Car	−0.027 (0.084)
Observations	2,796
Null Log Likelihood	−1,896.979
Log Likelihood	−1,178.442
McFadden's pseudo R^2	0.379
AIC	2,382.9
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.13 – Marginal model of car holding for the active sub-population

A much higher R^2 value appears for the car holding model reaching 0.38, meaning that 38% of the variance is explained by the model. Household location commune type, housing surface and income group variables have been found the most efficient variables to increase the log likelihood. The effect of the household commune type is strong, positive and gradually increasing with the distance from the agglomeration centre. So lower urbanized communes increase the likelihood of holding a car. The housing surface effect has a negative marginal effect because of the log-transformation, favouring car holding more for lower housing surface households than for higher housing surface households. The income group is also an important explanatory variable with a linear effect. Travel time differences are the only imposed explanatory variables related to the home-work trip. Among these, the difference illustrating the competition between car and PT is the most significant one, showing that the more the car is quicker than the PT for the home-work trip, the more cars are held.

Parking space holding model for the active sub-population

	Dependent variable (standard error):
	Parking space holding
Intercept	−6.351*** (0.423)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	1.146*** (0.135)
In-Agglomeration Urbanized	1.732*** (0.145)
In-Agglomeration Other	2.039*** (0.196)
Out-Agglomeration Main	1.585*** (0.215)
Out-Agglomeration Other	2.405*** (0.335)
Rural	1.792*** (0.295)
Log-transformed housing surface variable	
log(Housing Surface + 1)	0.858*** (0.107)
Income group variable	
Income	0.255*** (0.024)
Observations	2,796
Null Log Likelihood	−1,802.336
Log Likelihood	−1,552.968
McFadden's pseudo R^2	0.138
AIC	3,123.9
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.14 – Marginal model of parking space holding for the active sub-population

Along with the driving license holding model, the parking space holding model also does not have travel time difference components. All of its explanatory variables parameters are significant at 90%. The intercept value is strong and significantly negative for the reference population of individuals living in the city centre with small housing surfaces and in a low income group. The effect of the household location commune type is always strong and positive, so being out of the agglomeration centre indicates higher parking holding chances. This is consistent because parking holding is very expensive in the Paris city. More generally, being out of the main urbanized communes increases the parking holding chances too. The effect of the housing surface is complementary and strong, even though marginally decreasing because of the log-transformation. The final income variable has a linear positive effect, but not as strong as the previous ones. Like the driving license holding model, no home-work trip variable seems to be the main descriptors of parking space holding.

Motorcycle holding model for the active sub-population

	Dependent variable (standard error):
	Motorcycle holding
Intercept	−5.526*** (0.832)
Log-transformed housing surface variable	
log(Housing Surface + 1)	0.797*** (0.208)
Gender category variable(reference: Man)	
Woman	−1.779*** (0.243)
Workplace type category variable(reference: Office)	
Trade	0.718** (0.315)
Plants	0.247 (0.278)
Education	−0.930* (0.522)
Hospital	−0.040 (0.482)
Transport station	0.001 (0.622)
Individual	−13.51 (429.9)
Home	−12.94 (1,682)
Travel time differences variable	
Walk - Motorcycle	−0.005 (0.018)
Bike - Motorcycle	0.005 (0.058)
PT - Motorcycle	0.010** (0.005)
Car - Motorcyle	0.088 (0.078)
Observations	2,796
Null Log Likelihood	−707.311
Log Likelihood	−473.796
McFadden's pseudo R^2	0.330
AIC	975.6
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.15 – Marginal model of motorcycle holding for the active sub-population

The motorcycle holding model has a higher R^2 value at 0.33 and incorporates another home-work explanatory variable than the imposed travel time differences. The intercept is strongly negative, and the log-transformed housing surface, the gender and the workplace type are found to be the main explanatory variables to maximize the log likelihood along the travel time differences. So the effect of the housing surface is similar as for the previous parking space holding model, while the gender dummy variable points out that motorcycle is a gender unequal mobility tool. The workplace type variable highlights that individuals working in trade places are more likely to hold a motorcycle. Concerning travel time differences, only the difference between PT and motorcycles is significant, with individuals favouring motorcycle holding when the home-work trip is less long than with PT.

Bike holding model for the active sub-population

	Dependent variable (standard error):
	Bike holding
Intercept	−14.949 (324.744)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	0.296** (0.135)
In-Agglomeration Urbanized	0.712*** (0.152)
In-Agglomeration Other	0.563*** (0.214)
Out-Agglomeration Main	0.781*** (0.270)
Out-Agglomeration Other	1.032*** (0.398)
Rural	0.956** (0.439)
Log-transformed housing surface variable	
log(Housing Surface + 1)	0.611*** (0.108)
Socio-professional category variable(reference: Retired)	
No Activity	24.489 (459.257)
Employed	11.228 (324.744)
Blue Collar Worker	11.558 (324.744)
Intermediate Profession	11.713 (324.744)
Retailer	10.942 (324.744)
Executive	11.864 (324.744)
Travel time differences variable	
Walk - Bike	−0.008 (0.010)
Motorcycle - Bike	−0.024 (0.065)
PT - Bike	0.003 (0.003)
Car - Bike	0.003 (0.045)
Observations	2,796
Null Log Likelihood	−1,808.646
Log Likelihood	−1,387.026
McFadden's pseudo R^2	0.233
AIC	2,810.1
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.16 – Marginal model of bike holding for the active sub-population

To finish with the separate models for individual private mobility tools, the bike holding model is explained by household location commune type, the log-transformation of housing surface and the socio-professional category. The last variable is not significant, suggesting that bike holding is difficult to model for the active sub-population. Overall, the standard deviations are high for this model, making the model less reliable. The intercept appears to be not significant but rather negative. The household location commune type is significantly and positively explaining bike holding. The parameters are higher for communes out of the urban centre but not much higher in rural areas, so motorcycles appear to be held by households in the urban periphery. The housing surface has a decreasing positive effect on motorcycle holding compatible with the previous interpreting of the household location geographical effect. None of the travel time differences appear relevant for bike holding, and no home-work trip descriptor is included in the model, indicating a phenomenon not related with the home-work trip.

PT pass holding model for the active sub-population

	Dependent variable (standard error):
	PT subscription
Intercept	3.582*** (0.471)
Log-transformed housing surface variable	
log(Housing Surface + 1)	−0.879*** (0.117)
Workplace type category variable(reference: Office)	
Trade	−1.056*** (0.236)
Plants	−0.374* (0.214)
Education	−0.199 (0.181)
Hospital	−0.336 (0.225)
Transport station	−0.782* (0.425)
Individual	0.296 (0.454)
Home	−0.473 (1.449)
Workplace location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	−0.883*** (0.128)
In-Agglomeration Urbanized	−1.686*** (0.176)
In-Agglomeration Other	−1.990*** (0.263)
Out-Agglomeration Main	−2.966*** (0.596)
Out-Agglomeration Other	−15.561 (308.457)
Rural	−1.636*** (0.605)
Travel time differences variable	
Walk - PT	0.059*** (0.012)
Bike - PT	−0.185*** (0.039)
Motorcycle - PT	0.157** (0.078)
Car - PT	−0.011 (0.053)
Observations	2,796
Null Log Likelihood	−1,937.307
Log Likelihood	−1,159.945
McFadden's pseudo R^2	0.401
AIC	2,357.3
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.17 – Marginal model of PT pass holding for the active sub-population

The PT pass holding separate model for the active sub-population is efficient because it has a R^2 at 0.40, which is relatively high for a socio-economic model. It also involves several home-work trip descriptor variables such as workplace type category and workplace location commune effect, along significant effects of travel time differences. The intercept is significantly positive, so the individuals working in an office in the agglomeration centre with a low housing surface are more likely to hold a PT pass. The higher the housing surface, the lower the likelihood of holding a PT pass, but with a decreasing effect. Working in an office seems to favour PT pass holding while working in a shop decreases it, probably because office workers benefit from PT pass reimbursements from big companies while it is not the case when working in a small shop. Overall, the further away from the city centre the workplace is, the less PT passes are held. Travel time differences between PT and walk, bike and motorcycle are found significant: the more competitive the PT is with walking and motorcycles, the more likely a PT pass is held while it is the reverse with bike, which is difficult to explain.

Bike sharing subscription holding model for the active sub-population

Last, the bike sharing separate holding model for the active sub-population must be accounted for carefully because its standard deviations are high, because of the low diffusion of this mobility tool in 2010. A lot of the explanatory variables are not significant and the main explanatory descriptors are when the household or the workplace is in the city centre, where the service is available. So the home-work trip has an effect on this mobility tool holding choice to some extent. The R^2 is high at 0.35, especially for a model with so few significant explanatory variables.

Cross-analysis of the separate models for the active sub-population

Following the method employed for studying separate models on the whole sub-population, a summary of these models appears in Table 5.19.

Overall, the models are segmented between mobility tools directly associated with a mode use with higher R^2 values between 0.33 and 0.40 while the other models for parking space and driving license holding have R^2 values under 0.15. It remains unclear whether this is caused by the active sub-population segmentation or by the introduction of home-work trip explanatory variables. In both cases, it is consistent to state that the mobility need is causing this R^2 value increase, whether it is the mobility need generally associated with the active sub-population or with the home-work trip characteristics.

Except for the motorcycle, bike and bike sharing subscription mobility tools, most

	Dependent variable (standard error):
	Bike Sharing subscription
Intercept	−17.71(1.075e+04)
Household location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	−1.033*** (0.246)
In-Agglomeration Urbanized	−2.419*** (0.569)
In-Agglomeration Other	−2.484** (1.061)
Out-Agglomeration Main	−15.03 (934.9)
Out-Agglomeration Other	−15.02 (1,518)
Rural	−14.57 (1,601)
Socio-professional category variable(reference: Retired)	
No Activity	0.161 (1.521e+04)
Employed	15.32 (1.075e+04)
Blue Collar Worker	14.99 (1.075e+04)
Intermediate Profession	15.75 (1.074e+04)
Retailer	−0.690 (1.096e+04)
Executive	16.43 (1.075e+04)
Workplace location commune category variable(reference: Agglomeration Center)	
In-Agglomeration Dense	−0.704*** (0.259)
In-Agglomeration Urbanized	0.029 (0.424)
In-Agglomeration Other	0.493 (0.647)
Out-Agglomeration Main	−13.23 (1,110)
Out-Agglomeration Other	−14.25 (2,047)
Rural	−14.87 (1,699)
Travel time differences variable	
Walk - Bike	−0.027 (0.036)
Motorcycle - Bike	−0.275 (0.251)
PT - Bike	−0.012 (0.017)
Car - Bike	0.243 (0.176)
Observations	2,796
Null Log Likelihood	−543.805
Log Likelihood	−353.688
McFadden's pseudo R^2	0.350
AIC	753.4
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.18 – Marginal model of bike sharing subscription for the active sub-population

of the parameters are significant. The low share of motorcycle and bike sharing subscription, and the difficulty to represent bike holding explain this observation. The variables that are found in most of the models are the household location and the housing surface, each represented five times. They highlight the importance of geographical factors on the mobility tool holding phenomenon. The income variable is also represented three times, but only for car-related equipments: the driving license, the car and the parking space. It justifies the general consumption good approach used for car modelling. Last, the workplace location does not appear very often, but for both of the two mobility services mobility tools. This is related to the services coverage: the lower the level of service of a mobility service for the commune type of the workplace is, the lower the likelihood of holding the mobility service subscription. More generally, the PT and bike sharing mobility services subscription seem more related to home-work trip explanatory variables than other mobility tools.

Now that all of the separate model results are available, it is possible to compare these to display common and opposed patterns to better understand the mobility tool holding phenomenon.

5.2.3 Comparison of the results

This comparison subsection builds on the separate model results from both the whole and the active sub-population to illustrate mobility tools holding descriptors. It first compares both separate models approach, before using the knowledge gathered to analyse other applied or theoretical mobility tools holding models.

Accounting for home-work trip characteristics in the separate models

The results are difficult to compare between models because they are not built on the same observations, and because most of the mobility tools are described by additional travel time differences variables for the active sub-population models. This segmentation automatically improves the R^2 value without implying that the explanatory variables are more significant. The following comparative analysis compares the active sub-population models to the whole sub-population models, mobility tool by mobility tool and then overall.

While the driving license, car and parking space models have the same three main explanatory variables across the two models, it seems that the active sub-population restriction and the introduction of home-work trip characteristics do not impact these mobility tools holding much. Otherwise, the explanatory variables for the other mobility tools experience some important changes.

For the motorcycle model, the housing type and occupation category variables are not any more the main ones for improving the log likelihood of the model and they are replaced by the log-transformed housing surface and the workplace type category. This last variable shows the importance of the work environment on motorcycle holding, while the household economical and geographical characteristics are synthesized within the surface variable. Motorcycles are more likely held by active individuals living in large surface housings and working in a trade, plant or station while they are less likely held for workers in a hospital or in an education building. The only variables remaining the same from the previous model is the gender dummy variable identifying this mobility tool as more masculine than feminine, with significant holding gender inequalities.

While the bike holding model for the whole sub-population was mostly based on housing surface and age explanatory variables, this new model completely changes but without workplace characteristics. It means that the focus on the active sub-population is the cause of this change and not the added home-work trip characteristics. The age variable has probably lost some significance because the active population is also younger than the average sub-population which has a high share of retired individuals. The new selected explanatory variables are the household location commune type category, the log-transformed household surface and the socio-professional category. The first one suggests that the less urbanized the household commune is, the more likely it is to hold a bike. This is corroborated by the housing surface variable indicating higher holding rates for housing with a higher surface and which are also more likely to enable indoor bike parking. Last, the socio-professional category has high positive parameter values indicating that almost any category is more likely to hold a bike than the retired one, without much difference among these categories.

The active PT pass subscription model still relies on the housing surface, but the household location commune type and the socio-professional category are not the main explanatory variables any more. They are replaced by workplace characteristics. Indeed, it seems that for the active sub-population, the workplace commune type and the workplace type are more important for determining PT pass holding. This suggests possible intermodal use to reach the PT, which would be the final mode to arrive at the workplace. The workplace commune type effect is almost identical with similar parameters than the previous household location commune type, and the reference office workplace type and individual workplace type are factors favoring PT pass subscription.

The last bike sharing subscription model is almost identical as the previous one, but replacing education level variable by the workplace location commune type, making two strictly geographical variables in the model. This means that bike sharing subscription is very influenced by geographical conditions, and probably mostly by the bike sharing service diffusion in the Paris region.

Lastly, looking at the travel time differences shows whether taking them into account is relevant for explaining mobility tools holding levels or not. While it does not seem very useful for describing bike sharing or bike holding, it has significant effects on PT pass subscription and car holding. For the first one, the travel time differences with the walk and bike modes seem to be the most significant travel time differences, while it is the travel time difference with PT for the car. The effect on motorcycle holding is moderate but it is the travel time difference with PT which is the most significant one. The parameters are both positive for car and motorcycle, meaning that the more competitive these modes are against PT, the more the associated car and motorcycle mobility tools are held. The effects are less clear for PT pass subscription. Even though it highlights that it is more selected when more competitive as opposed to the walk mode, it is the opposite effect as opposed with the bike mode which is difficult to explain.

The separate mobility tools modelling step adding home-work trip variables has enabled to draw different conclusions. First, it seems that driving license and parking space holdings are not much impacted by workplace type characteristics. Even though car holding follows a similar trend, it is very influenced by travel time competition with the PT for the home-work trip. The bike model suggests that bike holding does not much rely on workplace type characteristics or home-work trip travel times but the model changes mostly come from the study population restriction to active individuals. The motorcycle is moderately impacted by the workplace conditions as it only relies on one workplace type variable and only with a low significance on travel time differences. It remains a mode that is generally not much held by women. PT pass holding is heavily explained by workplace conditions, replacing the previous household location effects. At last, the bike sharing subscription is mostly a geographical phenomenon dependent from household and workplace location, mostly because the service was only available in the city centre in 2010.

Comparison with literature and applied models

The approach developed in this section mainly differentiates itself from the literature by the relatively high number of mobility tools considered. Indeed, most of the literature is limited to two or three mobility tools, and the highest number of mobility tools considered at the same time observed is four in Habib et al. (2018). The less common mobility tools modelled which have been included here are the parking space, the motorcycle and the bike sharing subscription. So developing models for these understudied mobility tools is already a contribution.

Focusing on the study population of one individual households has also not been observed in the literature, even though it is very practical for avoiding household interpersonal complex choices. This also avoids the complex cases of mobility tools with different holding levels, whether at the individual or household scale. Other studies have gotten around this issue by aggregating the data at the household scale and considering household decisions, or have built proxy variables assigning household equipments to a household individual based on several criteria to keep studying the choice at the individual scale. But these introduce errors while the presented study population approach avoid them. But a large enough data set is required to make this population restriction, which is not always the case.

Considering home-work trip constraints on the mobility tool holding choice is also an important improvement proposed in this section. The impact of the travel time differences is significant for car and PT pass holding, as an indicator of competition with other modes. Home-work trip indicators seem to be of more importance for mobility services subscription than for private vehicle holding though.

Aside the general singularities of this research, the models employed generally are not as much developed as for studies on one mobility tool. They are still more detailed than aggregated consumption models such as in Cramer (1959), enabling several variables to describe the choice, but they are not as detailed as disaggregated dynamic models. Representing only one of these mobility tools would have required an extended variable and calibration approach, but this does not fit the aim of getting an overview of the holding models. Even taken one by one, the separate models are sufficient to have a quick analysis of the main explanatory variables for a mobility tool holding.

The separate holding models are similar to the mobility tools holding sub-models used in Antonin 3, the model for the Paris region owned by Ile-de-France Mobilités. These also are multinomial logits dealing with each mobility tools one by one, but with a more optimized calibration of each sub-model as it has been designed to be directly applied. But these models are sequenced together, so they are not completely separate, even if their individual functioning is.

Otherwise, some results confirm previous literature results, especially the high income effect for car-related mobility tools, validating the consumption approach often used for representing this mobility tool. The importance of the service availability for mobility services subscription has also been put forward by the many geographical explanatory variables directly linked with the accessibility of these services. Last, the effect of being in a physically able age range is also an intuitive result for studying bike and motorcycle holding.

Mobility tool modelled	McFadden's Pseudo R2	AIC	Variables
Driving License	0.12	2,063	Household location commune category Squared income group Log-transformed education level
Car	0.38	2,383	Household location commune category Log-transformed housing surface Income group Home-work trip walk travel time - Car travel time Home-work trip bike travel time - Car travel time Home-work trip PT travel time - Car travel time Home-work trip motorcycle travel time - Car travel time
Parking space	0.14	3,124	Household location commune category Log-transformed housing surface Income group
Motorcycle	0.33	976	Log-transformed housing surface Gender category Workplace type category Home-work trip walk travel time - Motorcycle travel time Home-work trip bike travel time - Motorcycle travel time Home-work trip PT travel time - Motorcycle travel time Home-work trip car travel time - Motorcycle travel time
Bike	0.23	2,810	Household location commune category Log-transformed housing surface Socio-professional category Home-work trip walk travel time - Bike travel time Home-work trip PT travel time - Bike travel time Home-work trip motorcycle travel time - Bike travel time Home-work trip car travel time - Bike travel time
PT Pass	0.40	2,357	Log-transformed housing surface Workplace type category Wokrplace location commune category Home-work trip walk travel time - PT travel time Home-work trip Bike travel time - PT travel time Home-work trip motorcycle travel time - PT travel time Home-work trip car travel time - PT travel time
Bike Sharing	0.35	753	Household location commune category Socio-Professional category Workplace location commune category Home-work trip walk travel time - Bike travel time Home-work trip PT travel time - Bike travel time Home-work trip motorcycle travel time - Bike travel time Home-work trip car travel time - Bike travel time

Table 5.19 – Results of the marginal models for the active sub-population

5.3 Portfolio Holding Models

Building on the analysis of separate models, this section upgrades the modelling approach of the mobility tool holdings phenomenon by considering multiple holding effects. Instead of building separate models, comprehensive models representing the holding interactions among several mobility tools are implemented. First, models on the sub-population of individuals living in one individual households are implemented, followed by a second subsection focusing on the active sub-population and a last general comparison of the models in a third section.

5.3.1 Portfolio holding models for the whole sub-population

This subsection begins by dealing with models for the restricted "Top 3" and "Traditional" mobility tools choice sets before addressing the more complete Full choice set.

5.3.1.1 The "Top 3" Multinomial Logit model

The setting of the choice alternatives of the "Top 3" combinations model is presented in Figure 5.6. It is worth observing that among the eight possible portfolios, two are very rare: the car without driving license and PT pass, and the car and PT pass without driving license. This is consistent with the driving license being a prerequisite for car holding as previously identified. The model results are available in Table 5.20, Table 5.21 and Table 5.22.

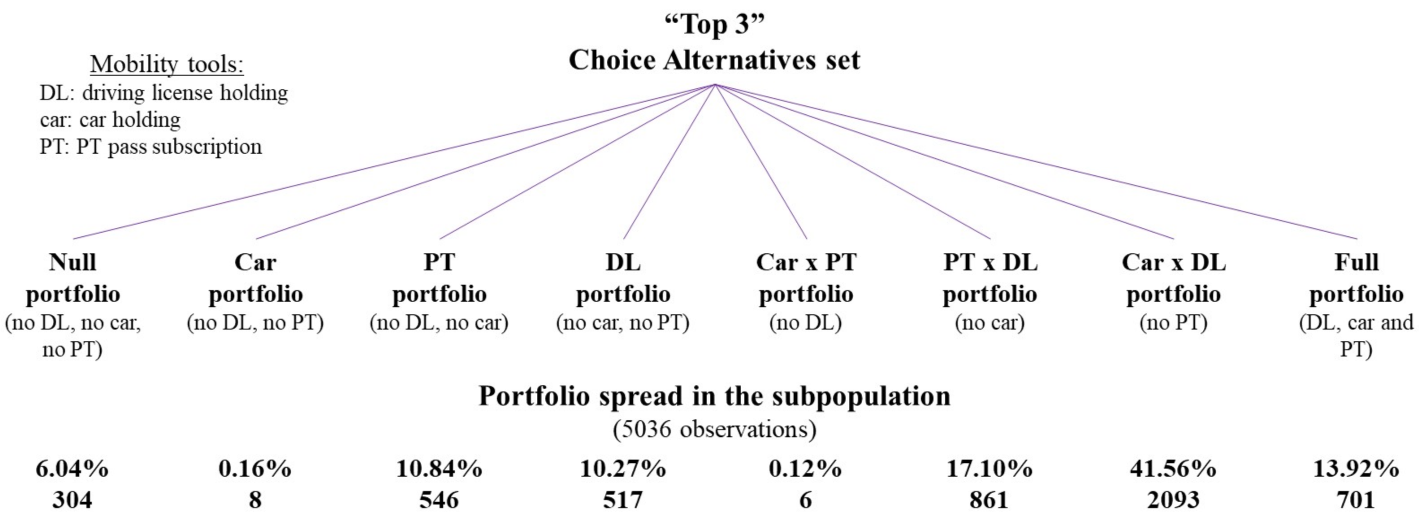


Figure 5.6 – Setting of the choice alternatives of the "Top 3" MNL model for the sub-population

	"Top 3" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Alternative Specific Constants		
Null	0 (Reference)	NA
Car	−7.160(2.745)	−2.61
PT pass	1.255(0.534)	2.35
Driving License	−1.001(0.574)	−1.74
Car x PT pass	−5.880(2.962)	−1.99
PT pass x Driving License	0.572(0.527)	1.09
Car x Driving License	−2.436(0.504)	−4.83
Car x PT pass x Driving License	−3.268(0.565)	−5.79
log(household location commune variable)		
Car	0.123(0.780)	0.16
PT pass	−0.818(0.158)	−5.18
Driving License	−0.881(0.162)	−5.44
Car x PT pass	0.495(0.870)	0.57
PT pass x Driving License	−1.734(0.157)	−11.06
Car x Driving License	0.756(0.142)	5.33
Car x PT pass x Driving License	0.016(0.157)	0.10
Age variable		
Car	0.005(0.033)	0.16
PT pass	−0.008(0.007)	−1.21
Driving License	0.014(0.07)	2.03
Car x PT pass	−0.027(0.039)	−0.69
PT pass x Driving License	−0.002(0.006)	−0.35
Car x Driving License	−0.004(0.006)	−0.61
Car x PT pass x Driving License	−0.000(0.007)	−0.06
Education level variable		
Car	0.053(0.180)	0.29
PT pass	0.098(0.035)	2.82
Driving License	0.232(0.037)	6.31
Car x PT pass	0.133(0.184)	0.72
PT pass x Driving License	0.258(0.034)	7.50
Car x Driving License	0.295(0.033)	9.07
Car x PT pass x Driving License	0.322(0.037)	8.76

Table 5.20 – "Top 3" portfolio MNL model for the sub-population (1/3)

	"Top 3" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Income category variable		
Car	0.311(0.202)	1.54
PT pass	0.015(0.046)	0.33
Driving License	0.204(0.044)	4.60
Car x PT pass	−0.076(0.264)	−0.29
PT pass x Driving License	0.199(0.043)	4.60
Car x Driving License	0.352(0.040)	8.77
Car x PT pass x Driving License	0.339(0.044)	7.78
Housing surface variable		
Car	0.008(0.013)	0.61
PT pass	−0.012(0.004)	−3.36
Driving License	−0.007(0.003)	−1.99
Car x PT pass	0.014(0.020)	0.71
PT pass x Driving License	−0.017(0.004)	−4.87
Car x Driving License	0.011(0.003)	3.67
Car x PT pass x Driving License	0.007(0.003)	2.14
Woman Gender indicator dummy variable (Reference: Man)		
Car	−0.008(0.769)	−0.01
PT pass	0.128(0.160)	0.80
Driving License	−0.295(0.162)	−1.83
Car x PT pass	0.300(0.903)	0.33
PT pass x Driving License	−0.164(0.154)	−1.06
Car x Driving License	−0.463(0.142)	−3.26
Car x PT pass x Driving License	−0.367(0.156)	−2.36
Daily number of trips variable		
Car	0.117(0.154)	0.76
PT pass	−0.007(0.035)	−0.21
Driving License	0.000(0.035)	0.01
Car x PT pass	0.235(0.150)	1.57
PT pass x Driving License	0.017(0.034)	0.51
Car x Driving License	0.123(0.030)	4.08
Car x PT pass x Driving License	0.059(0.034)	1.75

Table 5.21 – "Top 3" portfolio MNL model for the sub-population (2/3)

	"Top 3" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Occupation category variables(Reference: Retired)		
Worker dummy variable		
Car	1.358(1.201)	1.13
PT pass	0.694(0.264)	2.63
Driving License	0.040(0.260)	0.15
Car x PT pass	1.106(1.610)	0.69
PT pass x Driving License	0.744(0.254)	2.93
Car x Driving License	0.188(0.228)	0.83
Car x PT pass x Driving License	1.060(0.254)	4.17
Other dummy variable		
Car	1.055(1.351)	0.78
PT pass	0.082(0.276)	0.30
Driving License	−0.151(0.275)	−0.55
Car x PT pass	−8.651(109.456)	−0.08
PT pass x Driving License	−0.495(0.287)	−1.73
Car x Driving License	−0.223(0.242)	−0.92
Car x PT pass x Driving License	−0.200(0.308)	−0.65
Housing type category variable(Reference: Collective housing)		
Individual housing dummy variable		
Car	0.745(1.034)	0.72
PT pass	−0.254(0.290)	−0.88
Driving License	0.049(0.268)	0.18
Car x PT pass	−9.017(86.287)	−0.10
PT pass x Driving License	−0.217(0.313)	−0.70
Car x Driving License	0.179(0.213)	0.84
Car x PT pass x Driving License	−0.170(0.254)	−0.67
Observations	5,036	
Null Log Likelihood	−10,472.07	
Log Likelihood	−6,884.79	
R^2	0.343	
Adjusted R^2	0.335	
AIC	13,923.57	

Table 5.22 – "Top 3" portfolio MNL model for the sub-population (3/3)

A first observation when looking at the "Top 3" model results is that the R^2 is relatively high at 0.34. Even though it is not directly possible to compare this with the previous separate models because they do not have similar structures or the same number of variables, joint modelling mobility tools seems to be efficient. As expected, the Alternative Specific Constants(ASCs) are very low for car without driving license portfolios because the latter is a car prerequisite. For other parameters, the car and the combined car and PT pass portfolios systematically have the higher standard errors and are not usually significant. The reference individuals are generally more likely to hold portfolios encompassing PT passes, except for the full portfolio, and the null portfolio is the third most selected portfolio. The utility value of these ASCs vary on a 4.5 utility variation scale when not considering the car without driving license portfolios.

When considering the parameters of other variables, it is possible to estimate their associated utility variation scale by multiplying the variable variation range to the parameters, and identifying the highest range difference. The variations all are on a 0.5 to 3.5 utility variation scale when not considering the marginal portfolios held by less than 0.5% of the sub-population. So the socio-economic variables all seem to have some impact on the overall alternatives utility ranking. This highlights again the importance of the selected socio-economic variables on the "Top 3" portfolios holding.

In order to understand the effect of each variable on the portfolio choice, studying the parameters by variable type enables understanding which alternative is favoured or not by a variable's value. The log of household location commune type shows more detailed results than the one in chapter 4. Indeed, driving license only portfolios are not decreasing with urbanization level but rather increasing, and it mostly is the growth of the combined car and driving license portfolio that is leading the general driving license decreased holding with urbanization effect. This can be interpreted as the car and driving license co-holding effect being strongly negatively linked with urbanization. At the opposite, the PT pass, driving license and combined PT pass and driving license portfolios are positively linked with urbanization. The full portfolio is not much linked with the urbanization level because its parameter value is close to zero and not significant.

The effect of age is less complex because almost every age parameter is negative and not very significant. This confirms a general trend of holding less mobility tools when getting old. The only positive parameters are for the car portfolio and for the driving license portfolio, which is intuitive for driving licenses which are not withdrawn easily and which can be considered as cumulative over the age. For the car, this observation probably comes from the fact that aged single individuals are more likely to formerly live with a car driver who is not in the household any more, leaving them with single car portfolios.

The education level is also easy to understand: every parameter is positive, so a general conclusion is that having a higher education level enhances the likelihood of holding any "Top 3" mobility tool, which is associated to a higher average portfolio size. This is also confirmed by the fact that larger mobility tools portfolios have higher parameters.

On the income category side, the trend is similar with the education level. It can be noticed that the portfolios encompassing car holding usually have much higher parameter values than others which suggests that these portfolios are more related to the income level than others, except for the combined car and PT pass portfolio. Indeed, this portfolio is the only one with a not significant negative value, and is a very under represented portfolio in the population.

The housing surface variable yields quite regular patterns with positive parameters for every portfolio encompassing car holding and negative ones for every other not encompassing car holding. So high housing surface are related to higher car holding likelihood and lower PT pass subscription likelihood.

Switching to individual fixed characteristics, the woman gender dummy variable was chosen with men as a reference to display gender inequalities in portfolios holding. The parameters are all negative except for the PT pass portfolio and the not significant combined car and PT pass portfolio. Larger portfolios encompassing car holding are associated with the most negative parameters. It appears that women are more likely to hold single PT pass portfolios than other portfolios as opposed to men.

The daily number of trips is an indicator of the mobility need of an individual. The parameters of portfolios not including car generally are close to 0, not associated with significant patterns, while the portfolios encompassing the car have higher parameters and are more sensitive to higher mobility needs. The full portfolio enabling the most versatile behaviours and intermodality is not very sensitive to this daily number of trips variable.

Looking at the two occupation category dummy variables, the worker dummy variable clearly favours larger portfolio while it is the reverse for the other dummy variable. This latter dummy variable does not show significant results.

Last, the individual housing dummy variable is not significant but every portfolio encompassing the PT pass subscription has negative parameter values, which is compatible with an association between individual housing and individual mobility tools holding.

Overall, this "Top 3" model reproduces some statistical observations of the previous chapter, but also enables a much finer analysis with different combinations of mobility tools patterns. But one of its main drawbacks is the lack of significance of the two portfolio alternatives under 0.5% which do not enable drawing conclusions on these. The next model presenting more traditional portfolios combining car, PT pass and bike is not concerned with this issue because the alternatives are all better diffused in the sub-population as can be seen in Figure 5.7.

5.3.1.2 The "Traditional" Multinomial Logit model

After this "Top 3" model, another model on a restricted choice set is implemented: the "Traditional" multinomial logit including the most studied mobility tools in the literature.

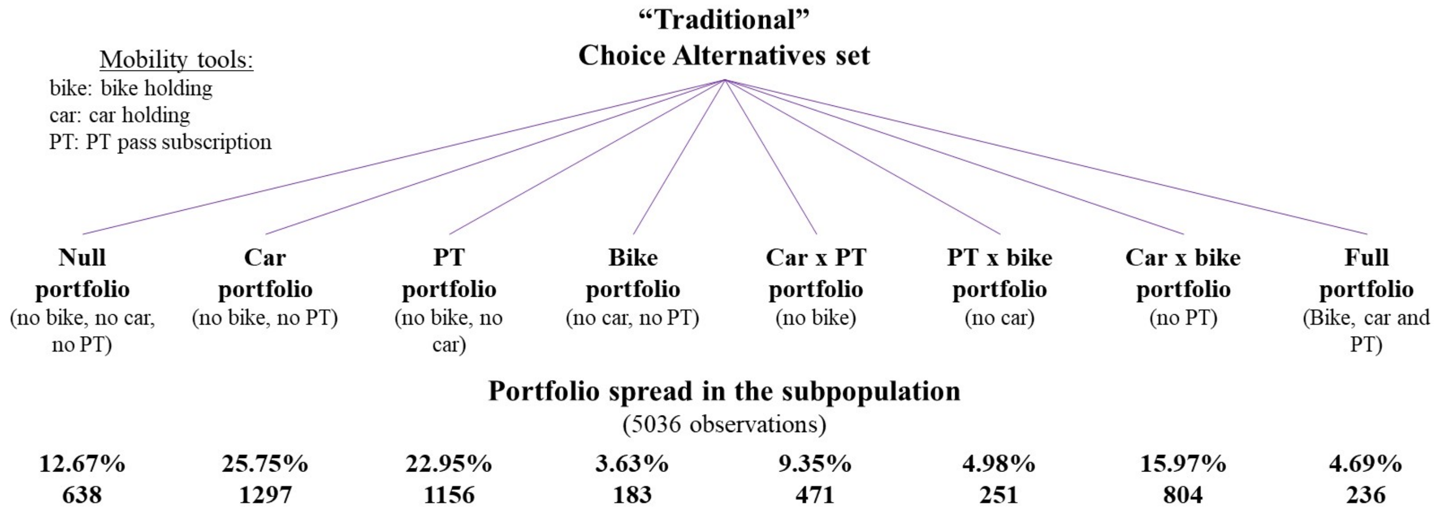


Figure 5.7 – Setting of the choice alternatives of the "Traditional" MNL model for the sub-population

The R^2 of the "Traditional" model is at 0.21, not as high as for the previous "Top 3" model, probably because of the less regular patterns observed for bike holding than for driving license holding. The ranking of the ASCs is similar, with the PT pass portfolio being the highest one quickly followed by the null portfolio.

	"Traditional" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Alternative Specific Constants		
Null	0 (Reference)	NA
Car	−2.493(0.428)	−5.83
PT pass	2.177(0.401)	5.42
Bike	−1.069(0.650)	−1.64
Car x PT pass	−2.877(0.518)	−5.55
PT pass x Bike	−2.432(0.612)	−3.97
Car x Bike	−3.701(0.491)	−7.53
Car x PT pass x Bike	−5.348(0.686)	−7.80
log(household location commune variable)		
Car	1.201(0.114)	10.56
PT pass	−0.841(0.114)	−7.36
Bike	−0.084(0.184)	−0.46
Car x PT pass	0.481(0.138)	3.48
PT pass x Bike	−0.460(0.170)	−2.71
Car x Bike	1.671(0.131)	12.76
Car x PT pass x Bike	1.016(0.175)	5.81
Age variable		
Car	−0.014(0.005)	−2.81
PT pass	−0.020(0.005)	−4.15
Bike	−0.028(0.008)	−3.55
Car x PT pass	−0.016(0.006)	−2.57
PT pass x Bike	−0.018(0.007)	−2.49
Car x Bike	−0.029(0.006)	−5.15
Car x PT pass x Bike	−0.018(0.007)	−2.38
Education level variable		
Car	0.151(0.026)	5.83
PT pass	0.027(0.025)	1.08
Bike	0.060(0.041)	1.48
Car x PT pass	0.157(0.033)	4.80
PT pass x Bike	0.191(0.039)	4.86
Car x Bike	0.188(0.030)	6.23
Car x PT pass x Bike	0.255(0.045)	5.70

Table 5.23 – "Traditional" portfolio MNL model for the sub-population (1/3)

	"Traditional" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Income category variable		
Car	0.200(0.028)	7.08
PT pass	−0.021(0.029)	−0.70
Bike	0.005(0.047)	0.10
Car x PT pass	0.178(0.035)	5.12
PT pass x Bike	0.032(0.042)	0.78
Car x Bike	0.217(0.032)	6.74
Car x PT pass x Bike	0.207(0.043)	4.79
Housing surface variable		
Car	0.016(0.002)	6.79
PT pass	−0.012(0.003)	−4.18
Bike	0.010(0.004)	2.66
Car x PT pass	0.012(0.003)	3.93
PT pass x Bike	0.003(0.004)	0.73
Car x Bike	0.020(0.003)	7.74
Car x PT pass x Bike	0.018(0.003)	5.41
Woman Gender indicator dummy variable (Reference: Man)		
Car	−0.311(0.110)	−2.84
PT pass	0.090(0.112)	0.81
Bike	−0.515(0.178)	−2.90
Car x PT pass	−0.278(0.133)	−2.08
PT pass x Bike	−0.325(0.160)	−2.03
Car x Bike	−0.596(0.123)	−4.85
Car x PT pass x Bike	−0.385(0.166)	−2.33
Daily number of trips variable		
Car	0.122(0.024)	5.05
PT pass	0.027(0.025)	1.08
Bike	0.115(0.039)	2.99
Car x PT pass	0.087(0.030)	2.91
PT pass x Bike	0.070(0.037)	1.89
Car x Bike	0.211(0.026)	8.03
Car x PT pass x Bike	0.108(0.037)	2.89

Table 5.24 – "Traditional" portfolio MNL model for the sub-population (2/3)

	"Traditional" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Occupation category variables(Reference: Retired)		
Worker dummy variable		
Car	0.204(0.176)	1.16
PT pass	0.609(0.182)	3.35
Bike	0.448(0.301)	1.49
Car x PT pass	1.044(0.220)	4.75
PT pass x Bike	1.646(0.297)	5.55
Car x Bike	0.465(0.201)	2.31
Car x PT pass x Bike	1.362(0.285)	4.78
Other dummy variable		
Car	0.013(0.203)	0.06
PT pass	−0.224(0.208)	−1.08
Bike	0.308(0.333)	0.93
Car x PT pass	0.027(0.290)	0.09
PT pass x Bike	0.793(0.351)	2.26
Car x Bike	−0.348(0.259)	−1.34
Car x PT pass x Bike	−0.525(0.519)	−1.01
Housing type category variable(Reference: Collective housing)		
Individual housing dummy variable		
Car	0.062(0.187)	0.33
PT pass	−0.266(0.249)	−1.07
Bike	0.737(0.298)	2.47
Car x PT pass	−0.064(0.253)	−0.25
PT pass x Bike	0.445(0.331)	1.35
Car x Bike	0.651(0.200)	3.25
Car x PT pass x Bike	−0.066(0.301)	−0.22
Observations	5,036	
Null Log Likelihood	−10,472.07	
Log Likelihood	−8,272.88	
R^2	0.210	
Adjusted R^2	0.203	
AIC	16,699.77	

Table 5.25 – "Traditional" portfolio MNL model for the sub-population (3/3)

The portfolio encompassing car only has a better ranking because it is not any more a car without driving license portfolio. The full portfolio seems to be the less preferred one for the reference population. The range of utility variation is of 7.4 for the ASCs, while the other parameters have utility variation ranges between 0.9 and 3.2. The parameters of these variables are lower than in the previous model compared with the range of variation for the ASCs, which is consistent with the lowest R^2 observed. Indeed, the model relies more on the fixed components because it is not able to well explain the variance.

The log of household location commune type is similar with the previous study, with car holding being strongly positively associated with this variable because each portfolio encompassing car holding has significant positive parameters, while bike holding is not very sensitive to it and PT pass holding significantly decreases in more rural areas.

Slightly different results can be observed for the age variable which displays only negative parameters showing a general equipment abandonment phenomenon with age, especially for mobility tools incurring maintenance costs. Bikes would have been expected to be more sensitive to the age variable because they require some physical condition. But this mobility tool can easily be stored without maintenance costs in a house so that is probably why its parameter is not stronger.

The education effect is the same than previously with only positive parameter values increasing with the portfolio size. This suggests an average higher portfolio size for the most educated individuals.

While PT pass and bike holding do not seem to be very sensitive to income variations, the portfolios encompassing the car have high positive parameter values, confirming again the fact that car holding is dependent on income levels. The other two mobility tools are not as expensive and the PT pass has a social pricing explaining its low sensitivity to the income variable.

The housing surface seems to be more positively related with car holding, then with bike holding and negatively related with PT pass holding. This ranking also appears in the portfolio mixing these, without much co-holding effects. This highlights again the interest of this surface variable mixing geographical location characteristics with income characteristics, in line with more regular patterns.

The woman gender dummy variable has again negative parameter for every portfolio except the PT only one, but which is not significant. So again, it seems that women are more likely to hold the null portfolio illustrating the gender inequality in mobility tools holding. The daily number of trips variable has a similar interpreting as for the previous model.

The dummy variables on occupation category confirm that being a worker improves the likelihood of holding any portfolio, especially these encompassing PT pass holding which probably comes from the regulations making firms pay for at least half of the PT pass subscription of their employees. The other occupation variable to differentiate from retired and worker sub-populations seems to be negatively associated with larger portfolios, not much affecting others except the combined PT pass and bike portfolio which is favoured. This might come from the fact that students with lower financial capacities to hold larger portfolios are included within this category.

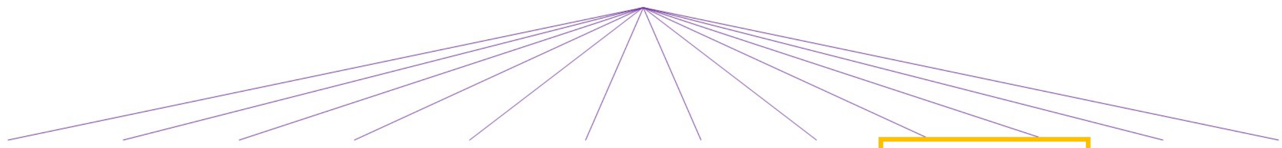
The last variable is the one on the individual housing category. It seems that the bike mobility tool is the most favoured in individual housings, with a higher positive parameter for every bike encompassing portfolio while PT pass holding is decreased by it for every portfolio. The combined car and bike portfolio seems to be the most favoured one in individual housings, which is also associated with lower urbanized household commune locations and higher in-house parking availability likelihood.

This traditional model, even though very close to the previous "Top 3" model, illustrates different patterns. First, the new model does not produce an equivalent R^2 with the same explanatory variables. Second, the values of the parameters change a lot with the definitions of the portfolio alternatives. It shows that even a replacement of only one mobility tool in the set of mobility tools for a MNL model changes a lot the results and interpreting of the model. Still common effects appear in both, especially the education effect increasing the likelihood of holding larger portfolios, the gender effect diminishing the portfolio size for women, and the age effect which also diminishes the portfolio size and favours null portfolio holding.

5.3.1.3 The Full Multinomial Logit model

After the first approach on reduced mobility tools portfolio choice sets, this new full MNL model aims on jointly addressing each of the seven study mobility tools holding. This objective is challenged by the number of possible portfolios

"Full MNL"
Choice Alternatives set



Portfolio composition

	Null	P1	P2	P3	P4	P5	P6	P7	P8 (Portfolios encompassing motorcycle)	P9 (Portfolios encompassing bike sharing)	P10	P11
Driving license	Ø	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Ø
Car	Ø	Ø	✓	✓	✓	✓	✓	Ø	✓	✓	Ø	Ø
Parking space	Ø	Ø	Ø	✓	Ø	✓	✓	Ø	✓	✓	Ø	Ø
Bike	Ø	Ø	Ø	Ø	✓	✓	Ø	✓	✓	✓	Ø	Ø
Motorcycle	Ø	Ø	Ø	Ø	Ø	Ø	Ø	Ø	✓	Ø	Ø	Ø
PT pass	Ø	Ø	Ø	Ø	Ø	Ø	✓	✓	✓	✓	✓	✓
Bike sharing	Ø	Ø	Ø	Ø	Ø	Ø	Ø	Ø	Ø	✓	Ø	Ø

Portfolio spread in the subpopulation

	Null	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
Subpopulation share	4.4%	7.1%	8.7%	15.7%	4.3%	9.8%	5.5%	2.9%	4.2%	3.0%	12.5%	9.1%
DM share	5.1%	8.1%	9.9%	18.0%	5.0%	11.3%	6.3%	3.3%	4.8%	3.48%	14.3%	10.4%
Observations	224	356	437	791	219	495	277	147	212	153	629	458

Figure 5.8 – Setting of the choice alternatives of the Full MNL model for the sub-population

with seven mobility tools going up to 128 – which can be reduced to 64 because parking space holding is only available for car holders –. Hopefully, the previous chapter stated that a set of 12 portfolios was enough to describe most of the mobility tools and most of the sub-population. The selected portfolios are presented in Figure 5.8. Attention must be paid to the specific portfolios P8 and P9 which are not exactly like the others, because these are general portfolios encompassing any portfolio respectively including motorcycle and bike sharing subscription holdings. Indeed, as these two mobility tools are a lot less common than the others and did not appear in the most represented portfolios, these options are similar to a mobility tool choice alternative among portfolio alternatives. Overall, the 12 selected portfolios are held by 87.3% of the sub-population which is significant even though not completely exhaustive. The explanatory variables used in this model are the same than in the reduced models, even though there are now 121 of them because of the increase of choice alternatives.

The overall model fits the data with a 0.19 R^2 which is similar to the R^2 of the separate mobility tools, even though the comparison is not straight because more variables are included in the Full MNL model. The study of the ASCs is consistent with the two reduced models: only the PT pass only or combined PT pass and driving license portfolios display higher values than the null portfolio reference for the reference sub-population: retired men living in collective housings in the city centre.

The first log of household commune location variable yields very distinct patterns for private vehicle mobility tools and PT pass holding: while all of the parameters for portfolios encompassing only private vehicles are significantly negative, all of the portfolios including PT pass holding combined with other mobility tools are significantly negative or not significant. The driving license only portfolio follows the same trend as PT pass encompassing portfolios. These results show that the urbanization levels are improving PT pass and driving license holding, while holding portfolios with private vehicle without PT pass decreases. This is consistent because urbanized areas are often associated with a higher PT accessibility improving PT pass holding rates.

The age variable also has effects which can be generalized: like for the reduced models, all of the parameters are significantly negative or not significant, except for the portfolios with driving license holding. Clearly, the ageing sub-population is more likely to have less mobility tools and portfolios in general than the younger one, because of different behaviours of demographic generations, or because the older populations are giving up their mobility tools with a reduced physical condition. This last statement seems more appropriate because the significant positive parameter value for the portfolio with driving license only tells that even though less likely to hold a car, the aged sub-population is more likely to hold a driving license. As driving license holding is only useful for motor vehicle use, this probably means former car holding in several cases. A longitudinal analysis would be useful to sort this questioning out.

Again, the education variable has only positive parameters confirming the general observation that the education level improves the likelihood of being equipped, especially with the largest portfolios. The income category variable suggests the same pattern and that might be because both have some degrees of correlation. Except that the latter seems to have less effect on portfolios encompassing the PT pass which have smaller values than observed for the education variable.

The household type variable does not give much information because it seems to be mirroring the log of household location commune type, with similar param-

	"Full" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Alternative Specific Constants		
Null	0 (Reference)	NA
P1	−0.911(0.703)	−1.30
P2	−1.590(0.674)	−2.36
P3	−3.891(0.661)	−5.89
P4	−4.979(0.829)	−6.00
P5	−3.789(0.716)	−5.29
P6	−3.747(0.764)	−4.91
P7	−2.853(0.877)	−3.25
P8	−3.333(0.826)	−4.04
P9	−3.224(0.923)	−3.49
P10	1.557(0.629)	2.48
P11	2.066(0.629)	3.28
log(household location commune variable)		
P1	−0.505(0.188)	−2.68
P2	0.616(0.184)	3.35
P3	0.819(0.175)	4.67
P4	1.194(0.221)	5.39
P5	1.190(0.191)	6.23
P6	0.002(0.203)	0.01
P7	−1.237(0.245)	−5.06
P8	0.043(0.220)	0.20
P9	−2.120(0.271)	−7.83
P10	−1.621(0.181)	−8.96
P11	−0.727(0.180)	−4.04
Age variable		
P1	0.010(0.008)	1.23
P2	−0.019(0.008)	−2.40
P3	0.001(0.008)	0.09
P4	−0.020(0.010)	−2.08
P5	−0.030(0.008)	−3.59
P6	−0.004(0.009)	−0.47
P7	−0.007(0.010)	−0.68
P8	−0.025(0.010)	−2.63
P9	−0.020(0.010)	−1.94
P10	−0.014(0.008)	−1.85
P11	−0.017(0.008)	−2.25

Table 5.26 – "Full" portfolio MNL model for the sub-population (1/4)

	"Full" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Education level variable		
P1	0.205(0.044)	4.69
P2	0.255(0.043)	5.92
P3	0.318(0.041)	7.71
P4	0.361(0.053)	6.80
P5	0.331(0.045)	7.34
P6	0.303(0.049)	6.17
P7	0.371(0.059)	6.34
P8	0.138(0.052)	2.65
P9	0.407(0.064)	6.35
P10	0.226(0.041)	5.57
P11	0.066(0.041)	1.62
Income category variable		
P1	0.152(0.052)	2.94
P2	0.200(0.052)	3.86
P3	0.390(0.048)	8.08
P4	0.269(0.059)	4.57
P5	0.382(0.051)	7.43
P6	0.339(0.055)	6.20
P7	0.204(0.062)	3.30
P8	0.418(0.061)	6.85
P9	0.316(0.063)	5.01
P10	0.158(0.050)	3.16
P11	−0.010(0.053)	−0.18
Housing surface variable		
P1	−0.002(0.004)	−0.48
P2	0.006(0.004)	1.41
P3	0.017(0.004)	4.80
P4	0.013(0.004)	2.97
P5	0.021(0.006)	5.71
P6	0.013(0.004)	3.15
P7	−0.002(0.006)	−0.35
P8	0.015(0.005)	3.36
P9	−0.002(0.006)	−0.32
P10	−0.015(0.004)	−3.62
P11	−0.010(0.004)	−2.38

Table 5.27 – "Full" portfolio MNL model for the sub-population (2/4)

	"Full" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Woman Gender indicator dummy variable (Reference: Man)		
P1	−0.353(0.199)	−1.78
P2	−0.547(0.191)	−2.86
P3	−0.566(0.183)	−3.10
P4	−0.887(0.219)	−4.05
P5	−0.680(0.194)	−3.51
P6	−0.626(0.207)	−3.02
P7	−0.916(0.239)	−3.84
P8	−2.287(0.256)	−8.97
P9	−0.765(0.241)	−3.18
P10	−0.334(0.187)	−1.79
P11	−0.087(0.192)	−0.45
Daily number of trips variable		
P1	0.004(0.042)	0.11
P2	0.135(0.040)	3.38
P3	0.115(0.038)	3.03
P4	0.207(0.045)	4.62
P5	0.219(0.040)	5.53
P6	0.109(0.044)	2.45
P7	0.088(0.053)	1.66
P8	0.178(0.047)	3.76
P9	0.164(0.052)	3.17
P10	0.047(0.040)	1.17
P11	0.026(0.041)	0.64
Occupation category variables(Reference: Retired)		
Worker dummy variable		
P1	−0.162(0.307)	−0.53
P2	0.464(0.298)	1.56
P3	0.066(0.279)	0.24
P4	1.201(0.357)	3.37
P5	−0.074(0.300)	−0.25
P6	0.950(0.322)	2.95
P7	1.475(0.406)	3.64
P8	2.199(0.422)	5.21
P9	1.660(0.441)	3.77
P10	0.580(0.292)	1.99
P11	0.629(0.298)	2.11

Table 5.28 – "Full" portfolio MNL model for the sub-population (3/4)

	"Full" portfolio MNL model for the sub-population	
	Parameter(standard error)	*t ratio*
Other dummy variable		
P1	−0.155(0.313)	−0.50
P2	0.302(0.312)	0.97
P3	−0.301(0.304)	−0.99
P4	0.228(0.433)	0.53
P5	−0.694(0.354)	−1.96
P6	−0.430(0.432)	−1.00
P7	0.653(0.465)	1.40
P8	1.144(0.503)	2.27
P9	0.277(0.563)	0.49
P10	−0.731(0.329)	−2.22
P11	0.090(0.305)	0.30
Housing type category variable(Reference: Collective housing)		
Individual housing dummy variable		
P1	−0.266(0.321)	−0.83
P2	−0.073(0.295)	−0.25
P3	0.091(0.265)	0.34
P4	0.568(0.321)	1.77
P5	0.610(0.278)	2.19
P6	−0.112(0.342)	−0.33
P7	0.536(0.457)	1.17
P8	1.083(0.331)	3.27
P9	−0.273(0.773)	−0.35
P10	−0.364(0.384)	−0.95
P11	−0.356(0.339)	−1.05
Observations	4,398	
Null Log Likelihood	−10,928.62	
Log Likelihood	−8,811.92	
R^2	0.194	
Adjusted R^2	0.183	
AIC	17,865.84	

Table 5.29 – "Full" portfolio MNL model for the sub-population (4/4)

eter values but less modalities.

Being a woman seems to be a negative factor for holding every portfolio, and even more for motorcycle holding. The only portfolio where this negative value is not significant is the PT pass portfolio, so it is reasonable to assume that all of the private mobility tools seems to carry gender holding inequalities.

The daily number of trips considered as a mobility demand indicator did not yield very distinct results for the first "Top 3" reduced model. The Full MNL model only shows positive parameter values indicating that this variable favours mobility tools holding in general, which is consistent with the preconception of this variable as a mobility demand indicator. But it seems to be less significant for portfolios encompassing PT pass holding than for other private vehicle holding portfolios.

Living in an individual housing seems to favour large portfolios encompassing private vehicle holding while decreasing combined and uncombined PT pass and driving license portfolios. This can be interpreted in line with the household location commune type because individual housings are more spread in rural and suburban areas.

At last, the occupation dummy variables highlight that being a worker is only associated with positive or insignificant parameters. So working generally supports mobility tools holding, and the most supported one is probably the motorcycle with the highest parameter value. Portfolios including parking space holding seem to be the ones with insignificant parameter values, suggesting that working has less effect on holding this mobility tool. The other occupation dummy variable has no regular parameter value pattern so it is more difficult to interpret, especially as it gathers several different occupation types.

While the previous analyses have enabled to study pieces of the mobility tools holding phenomenon for the seven study mobility tools, this last model gives an overview of the effects of different socio-economic variables on each mobility tool and enables drawing general trends. At the opposite of the former separate mobility tool models, it displays the complex relationship of multiple mobility tools holding and enables getting more consistent calibrations for forecasting several mobility tools within the same travel demand model.

Traditional MNL model portfolio spread in the active subpopulation
(2796 observations)

Null portfolio (no bike, no car, no PT)	Car portfolio (no bike, no PT)	PT portfolio (no bike, no car)	Bike portfolio (no car, no PT)	Car x PT portfolio (no bike)	PT x bike portfolio (no car)	Car x bike portfolio (no PT)	Full portfolio (Bike, car and PT)
7.12%	**22.46%**	**23.86%**	**3.72%**	**11.66%**	**6.76%**	**17.85%**	**6.58%**
199	**628**	**667**	**104**	**326**	**189**	**499**	**184**

Full MNL model portfolio spread in the active subpopulation

	Null	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
Driving license	Ø	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Ø
Car	Ø	Ø	✓	✓	✓	✓	✓	Ø	✓	✓	Ø	Ø
Parking space	Ø	Ø	Ø	✓	Ø	✓	✓	Ø	✓	✓	Ø	Ø
Bike	Ø	Ø	Ø	Ø	✓	✓	Ø	✓	✓	✓	Ø	Ø
Motorcycle	Ø	Ø	Ø	Ø	Ø	Ø	Ø	Ø	✓	Ø	Ø	Ø
PT pass	Ø	Ø	Ø	Ø	Ø	Ø	✓	✓	✓	✓	✓	✓
Bike sharing	Ø	Ø	Ø	Ø	Ø	Ø	Ø	Ø	Ø	✓	Ø	Ø
Active subpopulation share	2.2%	3.3%%	9.2%	11.4%	5.9%	9.0%	6.5%	3.8%	6.6%	4.5%	13.6%	8.3%
DM share	2.6%	3.9%	10.9%	13.6%	7.1%	10.8%	7.7%	4.6%	7.8%	5.3%	16.1%	9.8%
Observations	61	92	256	319	166	253	181	107	184	125	379	231

Figure 5.9 – Active sub-population portfolios spread for the "Top 3" and Full MNL models

5.3.2 Joint holding models for the active sub-population

The separate models have shown the interest of adding workplace characteristics and travel time differences for improving the representation of the mobility holding phenomenon in the second subsection. The added test variables are included in the joint models to observe their combined effect with the previous socio-economic variables. All of the workplace characteristics are tested except for the workplace type which involves too many dummy variables for the twelve portfolio alternatives. About the travel time differences, only the differences between car and PT travel times and between PT and bike travel times are considered. This decision has been made to avoid using too many variables and the difference between motorcycle and PT travel time, even though significant for motorcycle holding, has not been selected as the motorcycle mobility tool is not much spread and because this travel time difference is very close to the one between car and PT. As a result, 119 parameters are evaluated for the reduced model and 187 for the full MNL model based on 2,796 observations. Only one reduced model has been reproduced here because the previous "Top 3" model could not give much information on marginal portfolios including car without driving license, limiting the interest of using a portfolio analysis. The structures of the choice models remain the same as in the second section, but because the modelled population is the active sub-population, the portfolio shares are not the same any more. The portfolios spread in the active sub-population is presented in Figure 5.9.

5.3.2.1 The "Traditional" Multinomial Logit model for the active sub-population

When looking at the results of the Traditional MNL model, several observations can be made. First the R^2 is a little higher, but that does not mean much in itself because the model is too different from the previous one to compare. But there is no radical change in the model ability to explain the variance. The utility scale has changed a little. When the ASCs had a utility scale at about 7.4 with possible variations of individual variables between 0.9 and 3.2, it is now at 8.7 with range variations between 0.4 and 3.4 for the socio-economic variables, and range variations between 0.5 and 6.1 for the added workplace variables and 2.3 to 4.5 for the travel time variables. Clearly, the socio-economics have been diluted in the model but that was to be expected when adding new variables. The importance of the new variables seems quite significant as they have higher utility range scales.

Comparing the parameter values variable by variable for the socio-economics, it appears that the income, housing surface and individual housing have not experienced much change. The effect of the education variable has increased while all the other have decreased utility range scales.

For the log-transformed household location commune type, the parameters are now all positive, even though the car still is the main mobility tool driving this variable's effect with higher parameter values. It seems that active individuals living in less urbanized communes are more likely to hold several mobility tools while that is not directly the case for the whole sub-population. This can be explained by their added commuting mobility constraint.

The age is one of the variables that experiences the most important change, with all of its parameter becoming positive while they used to be negative in the former Traditional MNL model, yet with lower significance values. This is probably because the age scale of the active sub-population is not the same as for the whole sub-population. Because the active sub-population is generally more physically able than the aged one, ageing is more associated with higher social positions re-

	"Traditional" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Alternative Specific Constants		
Null	0 (Reference)	NA
Car	−5.458(0.669)	−8.16
PT pass	1.296(0.633)	2.05
Bike	−2.073(0.909)	−2.28
Car x PT pass	−3.185(0.733)	−4.35
PT pass x Bike	−2.720(0.821)	−3.31
Car x Bike	−7.430(0.723)	−10.28
Car x PT pass x Bike	−5.394(0.862)	−6.26
log(household location commune variable)		
Car	1.746(0.245)	7.13
PT pass	0.045(0.240)	0.19
Bike	0.376(0.362)	1.04
Car x PT pass	1.299(0.266)	4.89
PT pass x Bike	0.129(0.290)	0.45
Car x Bike	2.296(0.259)	8.86
Car x PT pass x Bike	1.838(0.301)	6.11
Age variable		
Car	0.024(0.008)	2.87
PT pass	0.006(0.008)	0.72
Bike	0.007(0.012)	0.56
Car x PT pass	0.011(0.009)	1.17
PT pass x Bike	0.015(0.010)	1.53
Car x Bike	0.018(0.009)	2.05
Car x PT pass x Bike	0.016(0.011)	1.51
Education level variable		
Car	0.166(0.049)	3.40
PT pass	0.065(0.048)	1.36
Bike	0.064(0.070)	0.92
Car x PT pass	0.175(0.056)	3.11
PT pass x Bike	0.290(0.065)	4.46
Car x Bike	0.252(0.053)	4.75
Car x PT pass x Bike	0.254(0.068)	3.76

Table 5.30 – "Traditional" portfolio MNL model for the active sub-population (1/5)

	"Traditional" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Income category variable		
Car	0.183(0.049)	3.73
PT pass	0.025(0.048)	0.51
Bike	0.070(0.069)	1.01
Car x PT pass	0.220(0.055)	4.01
PT pass x Bike	0.045(0.058)	0.77
Car x Bike	0.223(0.052)	4.28
Car x PT pass x Bike	0.247(0.063)	3.89
Housing surface variable		
Car	0.009(0.004)	2.03
PT pass	−0.020(0.005)	−4.24
Bike	−0.001(0.006)	−0.19
Car x PT pass	0.003(0.005)	0.67
PT pass x Bike	−0.004(0.006)	−0.78
Car x Bike	0.014(0.004)	3.18
Car x PT pass x Bike	0.009(0.005)	1.70
Woman Gender indicator dummy variable (Reference: Man)		
Car	0.063(0.178)	0.35
PT pass	0.268(0.174)	1.55
Bike	−0.075(0.253)	−0.30
Car x PT pass	0.309(0.197)	1.57
PT pass x Bike	−0.093(0.215)	−0.43
Car x Bike	−0.137(0.189)	−0.72
Car x PT pass x Bike	−0.026(0.227)	−0.11
Daily number of trips variable		
Car	0.098(0.040)	2.44
PT pass	−0.016(0.040)	−0.40
Bike	0.073(0.055)	1.34
Car x PT pass	0.010(0.046)	0.22
PT pass x Bike	−0.021(0.052)	−0.40
Car x Bike	0.142(0.042)	3.37
Car x PT pass x Bike	0.040(0.054)	0.74

Table 5.31 – "Traditional" portfolio MNL model for the active sub-population (2/5)

	"Traditional" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Housing type category variable(Reference: Collective housing)		
Individual housing dummy variable		
Car	0.276(0.478)	0.58
PT pass	0.435(0.517)	0.84
Bike	1.054(0.590)	1.79
Car x PT pass	0.399(0.520)	0.77
PT pass x Bike	0.595(0.593)	1.00
Car x Bike	0.946(0.476)	1.99
Car x PT pass x Bike	0.033(0.564)	0.06
Workplace unicity type category variable(Reference: Unique, Out of Home)		
Home dummy variable		
Car	1.107(0.417)	2.65
PT pass	−1.062(0.455)	−2.34
Bike	−0.299(0.579)	−0.52
Car x PT pass	−0.795(0.678)	−1.17
PT pass x Bike	−0.539(0.629)	−0.86
Car x Bike	0.576(0.515)	1.12
Car x PT pass x Bike	−1.042(1.074)	−0.97
Not unique dummy variable		
Car	1.063(0.343)	3.10
PT pass	−0.612(0.323)	−1.89
Bike	−0.214(0.486)	−0.44
Car x PT pass	−0.940(0.380)	−2.47
PT pass x Bike	−0.550(0.404)	−1.36
Car x Bike	1.289(0.369)	3.49
Car x PT pass x Bike	−0.918(0.443)	−2.07
Workplace location commune category variable		
Car	−0.096(0.105)	−0.91
PT pass	−0.602(0.118)	−5.11
Bike	−0.115(0.167)	−0.69
Car x PT pass	−0.812(0.130)	−6.27
PT pass x Bike	−0.720(0.151)	−4.76
Car x Bike	−0.069(0.108)	−0.65
Car x PT pass x Bike	−0.865(0.149)	−5.81

Table 5.32 – "Traditional" portfolio MNL model for the active sub-population (3/5)

	"Traditional" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Car parking availability at work dummy variable (Reference: Not Available)		
Car	0.867(0.240)	3.61
PT pass	0.090(0.225)	0.40
Bike	−0.184(0.320)	−0.57
Car x PT pass	−0.148(0.248)	−0.60
PT pass x Bike	−0.221(0.272)	−0.81
Car x Bike	0.840(0.259)	3.24
Car x PT pass x Bike	−0.199(0.280)	−0.71
Bike parking availability at work dummy variable (Reference: Not Available)		
Car	−0.081(0.230)	−0.35
PT pass	−0.211(0.223)	−0.95
Bike	0.347(0.330)	1.05
Car x PT pass	0.003(0.245)	0.01
PT pass x Bike	0.231(0.271)	0.85
Car x Bike	0.246(0.245)	1.00
Car x PT pass x Bike	0.135(0.276)	0.49
Home-work trip walk travel time variable		
Car	0.018(0.005)	3.77
PT pass	0.022(0.005)	4.58
Bike	0.006(0.006)	0.97
Car x PT pass	0.023(0.005)	4.80
PT pass x Bike	0.022(0.005)	4.13
Car x Bike	0.015(0.005)	3.03
Car x PT pass x Bike	0.023(0.005)	4.83
Home-work trip Bike - PT travel time variable		
Car	−0.045(0.027)	−1.65
PT pass	−0.039(0.027)	−1.44
Bike	−0.113(0.041)	−2.77
Car x PT pass	−0.042(0.027)	−1.55
PT pass x Bike	−0.044(0.029)	−1.52
Car x Bike	−0.032(0.027)	−1.15
Car x PT pass x Bike	−0.034(0.027)	−1.24

Table 5.33 – "Traditional" portfolio MNL model for the active sub-population (4/5)

	"Traditional" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Home-work trip PT - Car travel time variable		
Car	−0.011(0.024)	−0.46
PT pass	−0.028(0.024)	−1.19
Bike	−0.074(0.036)	−2.08
Car x PT pass	−0.016(0.024)	−0.69
PT pass x Bike	−0.013(0.025)	−0.49
Car x Bike	−0.001(0.024)	−0.03
Car x PT pass x Bike	−0.020(0.024)	−0.85
Observations	2,796	
Null Log Likelihood	−5,814.12	
Log Likelihood	−4,441.12	
R^2	0.236	
Adjusted R^2	0.216	
AIC	9,121.37	

Table 5.34 – "Traditional" portfolio MNL model for the active sub-population (5/5)

quiring more mobility and larger portfolios.

The effects of education, income, housing surface and daily number of trips are still similar, even though the utility scale of the education variable has improved, giving it more significance. At the opposite, the woman dummy variable has changed a lot: while the parameters were almost all significantly negative for this variable, most of them are not significant any more. This indicates that the gender inequality in mobility tools holding is less strong for active women than for women with other occupation categories.

The last socio-economic dummy variable dealt with individual housing and also used to be mostly made of negative parameters. These are all positive now, but can be interpreted in line with the explanation for the log-transformed household location commune type because this variable can be considered as a similar less detailed variable.

About workplace characteristics, it seems that working from home or having a not unique workplace have a similar effect, even though stronger for active individuals only working at home. The parameters indicate that these favour car and combined car and bike portfolios while decreasing PT portfolios holding. So these individuals rely on more individualized private mobility tools.

The workplace commune type has opposite trends with the household location. Individuals working in less urbanized communes have smaller portfolios. This may be because a lot of skilled and well-paid jobs are in urbanized areas, and so this variable captures social effects rather than geographical effects which would suggest the reverse. Concerning the parking facilities at the workplace, it seems that bike parking does not influence much the mobility tools portfolio, but that car parking availability clearly favours portfolios including the car. Whether car holding is increased by car parking availability or whether holding a car is what enables to work in workplaces with an available car parking space must be considered more specifically though.

Concerning the effect of travel times, the home-work trip walk travel time – linearly linked with the flying distance – has a significant positive effect on portfolio holdings, except for the bike portfolio which is positive but not significant. It induces a higher portfolio size for active individuals with a workplace far from their home, which may require more intermodal behaviours.

The final travel time differences are only associated with negative parameters with low significance values, which is probably caused by the stronger effect of the walk travel time variable.

To sum up, the model changes are small, except for the geographical parameters which have inverse effect depending on the household or workplace location, the age because the age scale changes for the active sub-population, and the gender which is not significant any more. The added workplace variables almost all have significant parameter values, except for the bike parking availability at work. This means that designing a specific model with workplace characteristics for the active sub-population makes sense and probably improves the socio-economic only model. Last, the effect of travel time variables seems to be mostly concentrated in the home-workplace distance rather than in travel time differences depending on the travel modes.

5.3.2.2 The Full Multinomial Logit model for the active sub-population

The full MNL model first shows similar patterns with higher utility scale and similar R^2 with the previous Full model. But there seems to be more parameter variation effects with higher range of utility scale: while the ASCs have a 10.8 range of utility scale, the variables have a range of utility scale between 0.7 and

	"Full" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Alternative Specific Constants		
Null	0 (Reference)	NA
P1	−1.917(1.256)	−1.53
P2	−4.341(1.102)	−3.94
P3	−8.498(1.125)	−7.55
P4	−8.067(1.207)	−6.69
P5	−9.789(1.175)	−8.33
P6	−4.791(1.178)	−4.07
P7	−4.773(1.296)	−3.68
P8	−3.869(1.153)	−3.36
P9	−5.535(1.375)	−4.03
P10	−0.641(1.072)	−0.60
P11	1.041(1.093)	0.95
log(household location commune variable)		
P1	−0.087(0.486)	−0.18
P2	1.014(0.420)	2.41
P3	1.671(0.421)	3.97
P4	2.021(0.447)	4.52
P5	2.023(0.433)	4.68
P6	1.007(0.437)	2.31
P7	−0.351(0.467)	−0.75
P8	0.859(0.434)	1.98
P9	−1.094(0.480)	−2.28
P10	−0.346(0.411)	−0.84
P11	0.281(0.421)	0.67
Age variable		
P1	0.016(0.016)	0.98
P2	0.023(0.014)	1.65
P3	0.048(0.014)	3.41
P4	0.027(0.015)	1.79
P5	0.033(0.015)	2.25
P6	0.027(0.015)	1.77
P7	0.034(0.016)	2.13
P8	0.014(0.015)	0.90
P9	0.025(0.016)	1.58
P10	0.022(0.014)	1.56
P11	0.013(0.014)	0.87

Table 5.35 – "Full" portfolio MNL model for the active sub-population (1/6)

	"Full" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Education level variable		
P1	0.268(0.092)	2.91
P2	0.254(0.080)	3.15
P3	0.408(0.082)	5.00
P4	0.398(0.088)	4.54
P5	0.511(0.086)	5.95
P6	0.314(0.088)	3.55
P7	0.511(0.101)	5.05
P8	0.148(0.086)	1.72
P9	0.632(0.115)	5.51
P10	0.311(0.080)	3.90
P11	0.070(0.081)	0.86
Income category variable		
P1	0.210(0.103)	2.03
P2	0.259(0.095)	2.72
P3	0.458(0.094)	4.85
P4	0.335(0.100)	3.37
P5	0.468(0.097)	4.83
P6	0.484(0.100)	4.85
P7	0.327(0.102)	3.22
P8	0.500(0.099)	5.06
P9	0.394(0.101)	3.91
P10	0.290(0.093)	3.13
P11	0.101(0.097)	1.04
Housing surface variable		
P1	0.009(0.008)	1.11
P2	0.004(0.007)	0.59
P3	0.016(0.004)	2.23
P4	0.015(0.007)	1.99
P5	0.022(0.007)	3.02
P6	0.011(0.008)	1.39
P7	−0.000(0.008)	−0.05
P8	0.014(0.007)	1.95
P9	−0.001(0.009)	−0.06
P10	−0.018(0.008)	−2.41
P11	−0.010(0.008)	−1.24

Table 5.36 – "Full" portfolio MNL model for the active sub-population (2/6)

"Full" portfolio MNL model for the active sub-population		
	Parameter(standard error)	*t ratio*
Woman Gender indicator dummy variable (Reference: Man)		
P1	$-0.239(0.349)$	-0.68
P2	$-0.206(0.309)$	-0.67
P3	$-0.290(0.308)$	-0.94
P4	$-0.342(0.328)$	-1.04
P5	$-0.292(0.318)$	-0.92
P6	$-0.040(0.327)$	-0.12
P7	$-0.734(0.348)$	-2.11
P8	$-2.059(0.359)$	-5.74
P9	$-0.597(0.343)$	-1.74
P10	$-0.146(0.302)$	-0.48
P11	$-0.005(0.313)$	-0.02
Daily number of trips variable		
P1	$-0.079(0.075)$	-1.06
P2	$0.016(0.063)$	0.26
P3	$0.075(0.063)$	1.20
P4	$0.108(0.066)$	1.64
P5	$0.075(0.065)$	1.16
P6	$-0.002(0.069)$	-0.03
P7	$-0.078(0.077)$	-1.01
P8	$0.094(0.066)$	1.43
P9	$0.022(0.073)$	0.30
P10	$-0.042(0.063)$	-0.67
P11	$-0.070(0.066)$	-1.06
Individual housing dummy variable		
P1	$-1.673(1.172)$	-1.43
P2	$-0.253(0.647)$	-0.39
P3	$-0.286(0.635)$	-0.45
P4	$0.423(0.641)$	0.66
P5	$0.240(0.634)$	0.38
P6	$-0.324(0.699)$	-0.46
P7	$0.433(0.774)$	0.56
P8	$0.882(0.640)$	1.38
P9	$-10.047(94.194)$	-0.11
P10	$-0.447(0.741)$	-0.60
P11	$0.208(0.675)$	0.31

Table 5.37 – "Full" portfolio MNL model for the active sub-population (3/6)

"Full" portfolio MNL model for the active sub-population		
	Parameter(standard error)	*t ratio*
Workplace unicity type category variable(Reference: Unique, Out of Home)		
Home dummy variable		
P1	−1.417(0.701)	−2.02
P2	0.490(0.622)	0.79
P3	−0.352(0.677)	−0.52
P4	−0.212(0.772)	−0.27
P5	−1.420(0.862)	−1.65
P6	−1.691(0.908)	−1.86
P7	−0.750(0.788)	−0.95
P8	0.040(0.710)	0.06
P9	−1.454(0.839)	−1.73
P10	−1.707(0.667)	−2.56
P11	−3.166(1.140)	−2.78
Not unique dummy variable		
P1	−0.919(0.681)	−1.35
P2	0.645(0.605)	1.06
P3	0.814(0.607)	1.34
P4	0.821(0.652)	1.26
P5	0.887(0.626)	1.42
P6	−1.160(0.635)	−1.83
P7	−0.644(0.672)	−0.96
P8	0.105(0.628)	0.17
P9	−0.636(0.651)	−0.98
P10	−0.808(0.579)	−1.40
P11	−1.179(0.600)	−1.97
Workplace location commune category variable		
P1	−0.088(0.219)	−0.40
P2	−0.060(0.175)	−0.34
P3	−0.088(0.175)	−0.51
P4	−0.101(0.179)	−0.57
P5	−0.027(0.176)	−0.15
P6	−0.744(0.199)	−3.75
P7	−0.642(0.229)	−2.80
P8	−0.522(0.189)	−2.76
P9	−0.624(0.245)	−2.55
P10	−0.676(0.191)	−3.55
P11	−0.603(0.190)	−3.17

Table 5.38 – "Full" portfolio MNL model for the active sub-population (4/6)

"Full" portfolio MNL model for the active sub-population		
	Parameter(standard error)	*t ratio*
Car parking availability at work dummy variable (Reference: Not Available)		
P1	−0.219(0.478)	−0.46
P2	0.525(0.443)	1.19
P3	0.715(0.444)	1.61
P4	0.466(0.474)	0.98
P5	0.483(0.455)	1.06
P6	−0.532(0.448)	−1.19
P7	−0.474(0.475)	−1.00
P8	−0.006(0.464)	−0.01
P9	−0.392(0.471)	−0.83
P10	0.002(0.426)	0.00
P11	−0.325(0.433)	−0.75
Bike parking availability at work dummy variable (Reference: Not Available)		
P1	−0.294(0.477)	−0.62
P2	−0.204(0.434)	−0.47
P3	−0.114(0.433)	−0.26
P4	0.193(0.461)	0.42
P5	0.152(0.445)	0.34
P6	−0.091(0.447)	−0.20
P7	0.443(0.482)	0.92
P8	0.164(0.462)	0.35
P9	0.037(0.470)	0.08
P10	−0.285(0.427)	−0.67
P11	−0.194(0.434)	−0.45
Home-work trip walk travel time variable		
P1	−0.009(0.010)	−0.82
P2	0.019(0.008)	2.44
P3	0.015(0.008)	1.84
P4	0.014(0.008)	1.79
P5	0.015(0.008)	1.88
P6	0.023(0.008)	2.91
P7	0.022(0.008)	2.67
P8	0.022(0.009)	2.83
P9	0.024(0.009)	2.83
P10	0.024(0.008)	3.13
P11	0.022(0.008)	2.77

Table 5.39 – "Full" portfolio MNL model for the active sub-population (5/6)

	"Full" portfolio MNL model for the active sub-population	
	Parameter(standard error)	*t ratio*
Home-work trip Bike - PT travel time variable		
P1	0.167(0.067)	2.51
P2	0.064(0.056)	1.15
P3	0.084(0.056)	1.50
P4	0.080(0.056)	1.43
P5	0.082(0.056)	1.46
P6	0.078(0.056)	1.39
P7	0.061(0.058)	1.04
P8	0.053(0.056)	0.95
P9	0.056(0.059)	0.95
P10	0.063(0.056)	1.13
P11	0.078(0.056)	1.38
Home-work trip PT - Car travel time variable		
P1	0.135(0.059)	2.29
P2	0.076(0.048)	1.59
P3	0.089(0.048)	1.85
P4	0.088(0.049)	1.80
P5	0.086(0.048)	1.79
P6	0.071(0.048)	1.48
P7	0.064(0.050)	1.29
P8	0.070(0.048)	1.46
P9	0.037(0.051)	0.73
P10	0.044(0.048)	0.92
P11	0.065(0.048)	1.35
Observations	2,796	
Null Log Likelihood	−5,849.47	
Log Likelihood	−4,643.51	
R^2	0.206	
Adjusted R^2	0.174	
AIC	9,661.02	

Table 5.40 – "Full" portfolio MNL model for the active sub-population (6/6)

10.9, indicating a potential high importance of the explanatory variables on the utility of a portfolio. As opposed to the previous full model, the parameters almost all have higher or equal ranges of utility scale.

Looking at the parameters of each variable into more detail suggests different results than from the Traditional MNL model on the active sub-population. Except for the age variable, all of the socio-economic variables have similar effects than in the previous full MNL model on the sub-population, with a negative shift for the daily number of trips parameters. So the interpreting stays the same for these. The new age parameters are explained the same way as previously, by the removal of the older and less physically able in sub-population.

The dummy variables describing working from home and having multiple workplaces display similar trends but with less negative parameters for the individuals with several workplaces. It seems that working at home has a general negative or not significant effect on holding every portfolio, with stronger negative values for portfolios encompassing PT pass holding and for the driving license holding portfolio. So workers staying at home are less equipped than the general sub-population, and even less regarding PT pass holding. This may be caused by the status of workers at home, because these could be liberal workers not benefiting from firm PT pass discounts as other employees do. Regarding the workers with several workplaces, they may be given company vehicles favouring the portfolios with private vehicles.

The workplace commune type is similar with the previous traditional MNL model, with only negative values. Its effects seem stronger on portfolios encompassing the PT pass. It means that individuals working in less urbanized areas have less mobility tools explained by lower PT pass holding shares. The car parking availability at the workplace again has a moderate effect favouring car holding while bike parking availability is not significant.

About the effect of travel times, the walk travel time indicates that the further apart home and workplace are, the more likely the individuals are to hold every portfolio because each parameter is positive or not significant. Concerning travel time differences, the parameters are also all positive but not very significant, without favouring specific portfolio types.

5.3.3 Comparison of the results of the separate mobility tool holding models

Generally speaking, restricting choice models is a relevant first approach to get a quick phenomenon overview. It enables limiting the number of studied portfolios and getting interaction relationships among these. But it completely ignores the relationship with other mobility tools: it is like looking at an object from one side only. Conducting several of these analyses can give the overall picture but it takes numerous models to do so. This emphasizes the importance of representing as much mobility tools as possible at the same time, to avoid missing significant relationships. The full portfolios approach is not technically a "Full" choice set, but it is representative of most of the portfolios and most of the mobility tools, so it remains a large enough analysis. Conducting this full portfolio analysis brings a lot of information but it is limited by the number of variables to consider, directly linked with the number of considered alternatives.

When opposed to separate models, the multiple holdings models developed in this section enable a quicker analysis of the effect of a variable on the portfolio equilibrium. While most of the results from the separate approach had to be made comparing seven different models with different intercepts and utility scales, this joint modelling approach yields immediately comparable parameters. These even easily show multiple holding effects when opposing parameters of single mobility tool portfolios to parameters of portfolio made of a combination of mobility tools.

Within this framework, improving the models with workplace characteristics has enabled to get a more refined analysis, without deteriorating the first results or the overall R^2. Including characteristics of a constrained trip seems to better explain the subscription to mobility services, which automatically improves the overall multiple holdings explanatory power. Other studies such as Le Vine et al. (2013); Astegiano et al. (2017); Plevka et al. (2018) emphasize the importance of activities on the mobility tools holding choice. But when these conceptualize mobility tools holding as an answer to a full Perceived Activity Set (PAS) demand, the present modelling approach makes the assumption that constrained trip characteristics matter the most.

Coming back to the comparison with the Antonin 3 model, Antonin 3 does not explicitly deal with multiple holdings effects. It considers a hierarchy of mobility tools and first models the driving license holding choice, then the car holding choice, the motorcycle holding choice and the PT pass holding choice, for the head of the household and for the other household members afterwards. The results of the former models are introduced as inputs for the latter ones, including a type of correlation effect difficult to single out and identify. This representing could probably be improved by considering these equipments altogether to clarify this correlation relationship, and to avoid optimizing results for each model, not ensuring the optimization of the overall mobility tools holding module while the joint model does. Even though Antonin 3 and the models built here have both been implemented on the EGT 2010 data set, directly using the models from this chapter would not be recommended because they have been designed for an exploratory purpose. But the results naturally lead to favouring the implementation of a joint model differentiating private vehicle holdings from mobility services, and a portfolio approach with the inclusion of the characteristics of constrained trips.

Conclusion

Building on separate mobility tool models identifying the three most relevant socio-economic variables describing each of the seven study mobility tools through the implementation of binary logits, this chapter has proposed model specifications dealing with joint mobility tools holding. These models have first been tested on a reduced choice set of mobility tools portfolios, before being applied to an extended choice set representing the majority of the portfolios observed in the sub-population. These involved the use of multinomial logit models enabling several choice alternatives. These steps have enabled studying the effect of socio-economic variables on holding portfolios instead of the isolated mobility tools, highlighting different effects, especially concerning the average portfolio size.

After this analysis, it has been observed that introducing trip characteristics of constrained activities with the example of the home-work tirp could improve the model, because the portfolio choice is not only based on socio-economic variables but also on the constraint to make some trips. Home-work trip travel times have been computed for the car, motorcycle, PT, bike and walk mode through the use of the MODUS model with the Transcad software. A first analysis of these results has enabled to identify the potential effect of these travel times on mobility tools holding, especially when considering their differences as competition indicator between modes. This step has also implied reducing the sub-population to the active sub-population.

Following the previous observation of the importance of the home-work trip on mobility tools holding, some workplace characteristics and home-work trip modal travel time and differences have been added in the model explanatory variables. These mostly have not changed the effects of previous socio-economic variables, but they have improved the representing of the phenomenon by displaying new social and geographical effects.

The models developed in this chapter have been used to investigate the mobility tools portfolio holding phenomenon, and not to forecast it. This step has highlighted effects of several important potential explanatory variables to be included for forecasting. The need to consider many mobility tools instead of a few has also been emphasized, and especially to focus on the relationship between several mobility tools holding to avoid simple reasoning directly linking PT subscription increase with car holding decrease, without considering the variation of another mobility tools holding.

While it would have been interesting to develop more complex model structures enabling correlation among errors such as nested logits or cross-nested logits, these have been tried and did not converge after several different nest structures tests. Even though there seems to be a mobility tools holding structure based on private vehicle and mobility services, this does not immediately translate into error correlation. Further research on how to implement this observed model structure in the econometric models is needed to build models better fitting the decision structure of the mobility tools portfolio holding choice.

Chapter 6

Representing Intermodality

Introduction

While the previous chapters dealt with the mobility tools holding phenomenon by linking it to the home-work trip mode choice, they focused on trips described by a single mode. But the emerging mobility services are intermediate and versatile solutions that can be considered as complementary with traditional modes, and not substitutes. This trend is favoured by the apparition of the Mobility as a Service (MaaS) mobility system concept aiming to reduce transfer costs among mobility networks and to consider all of the metropolitan transport networks as one multimodal network integrating all of them. These imply an evolution of the trip structure with the diffusion of more complex intermodal trips mixing several modes within the same trip, also fostered by regional lifestyle evolution according to Massot (1999). This type of flexible intermodal trip is also favoured by local authorities because intermodal trips often involve the use of public transit. As stated in Szyliowicz (2003), intermodal connections within a system improve its efficiency and its resilience, minimizing the negative impacts of separate transport systems. Systems favoring intermodality also foster modal economic competition, and bring additional travel alternatives to individuals. In the paper, Szyliowicz even expects a new paradigm associated to this intermodality phenomenon, making it a topic of high interest for the future developments of mobility systems, especially encouraged by a wide local mobility supply.

Thus, to better account for these in mobility demand models, specific care must be taken to identify what are the drivers and limits of this phenomenon, and what is its decision making structure. Indeed, studying intermodality is not straightforward and similar but different from studying traditional mobility. Where the trips used to be characterized by one main transport mode, they are now characterized by several. An immediate consequence is the high increase of alternative routes offered by such intermodal trips. This makes route choice more complex and deteriorates the trip route and travel time characterization which are key for choosing a trip mode. So addressing intermodality requires technical simplifications to avoid dealing with a too large number of potential routes. Mobility tools holding must also be jointly considered with new travel behaviours because it has a direct effect on the mode choice universe and therefore on mobility uses and the intermodal alternative availability.

The aim of this chapter is to analyse the complex intermodality demand phenomenon and how it can be integrated into metropolitan mobility models. Dealing with intermodality demand leads to fundamental questionings about what is a trip and how it is integrated within activity chains, and what is a mode. These are important for differentiating intermodality from multimodality while enabling to distinguish several ways of questioning the intermodality phenomenon. In order to answer this general challenge, it is necessary to set up the intermodality concept, to describe the phenomenon on a study case and to identify how it could be modelled.

To reach these goals, the representation of traditional trips is questioned and statistical analysis tools and modelling techniques are used to assess intermodality demand by modelling intermodal home-work trip mode choice. A first section focuses on a conceptualization of intermodality demand and intermodality modelling, and how it has formerly been addressed in the literature. The second section displays a statistical description of the phenomenon in the Paris region from individual and trip perspectives. The last third section offers a model specification and application, before discussing improvement for intermodality representation.

6.1 Concept and Literature Review

Before beginning to build statistical analyses on intermodality, the phenomenon must be defined in order to avoid misunderstandings and inappropriate generalization. This section first provides a definition of intermodality and discusses the limits of the concept and how it will be interpreted in this chapter. Second, it focuses on the description of the phenomenon and the characterization of its practitioners in the literature. Third, it introduces the intermodality modelling issue.

6.1.1 Intermodality definition

As exposed by Jones et al. (2000), several definitions of intermodality are often used by different entities depending on their concern about the phenomenon. After reviewing a few of these definitions, this paper proposes to define intermodality as "the shipment of cargo and the movement of people involving more than one mode of transport during a single, seamless journey". The "seamless" term is an important specification here, meaning that the journey is considered as a unit and not as the sum of several journeys. Crainic & Kim (2007) proposes another more freight-related definition: "the transport of a person or a load from its origin to its destination by a sequence of at least two transport modes, the transfer from one mode to the next being performed at an intermodal terminal" but also highlights that the intermodality phenomenon is diverse and has different meanings in the freight or metropolitan mobility fields.

As this dissertation deals with metropolitan mobility, the definition that is used – even though similar and related to the ones displayed in Jones et al. (2000); Crainic & Kim (2007) – is specifically developed and applied. Three main elements can be identified within the two proposed definitions: the unicity of the movement between an origin and a destination, the use of several modes, and a location where the mode change happens.

A few terms must be defined to avoid misunderstandings. In this dissertation, the movement of a person from a main activity origin point to a main activity destination point is called a trip, also often called a journey. The movement of a person from a main origin to a main destination and back is called a round trip. If other activity destinations such as grocery or another person's drop off are included within the round trip, it is called a tour or an activity chain. If a trip has an intermediate stop where there is a change of vehicle or transport mode without conducting a specific activity, the trip is subdivided among trip legs. Distinguishing an intermodal trip from a tour is sometimes difficult as an in-

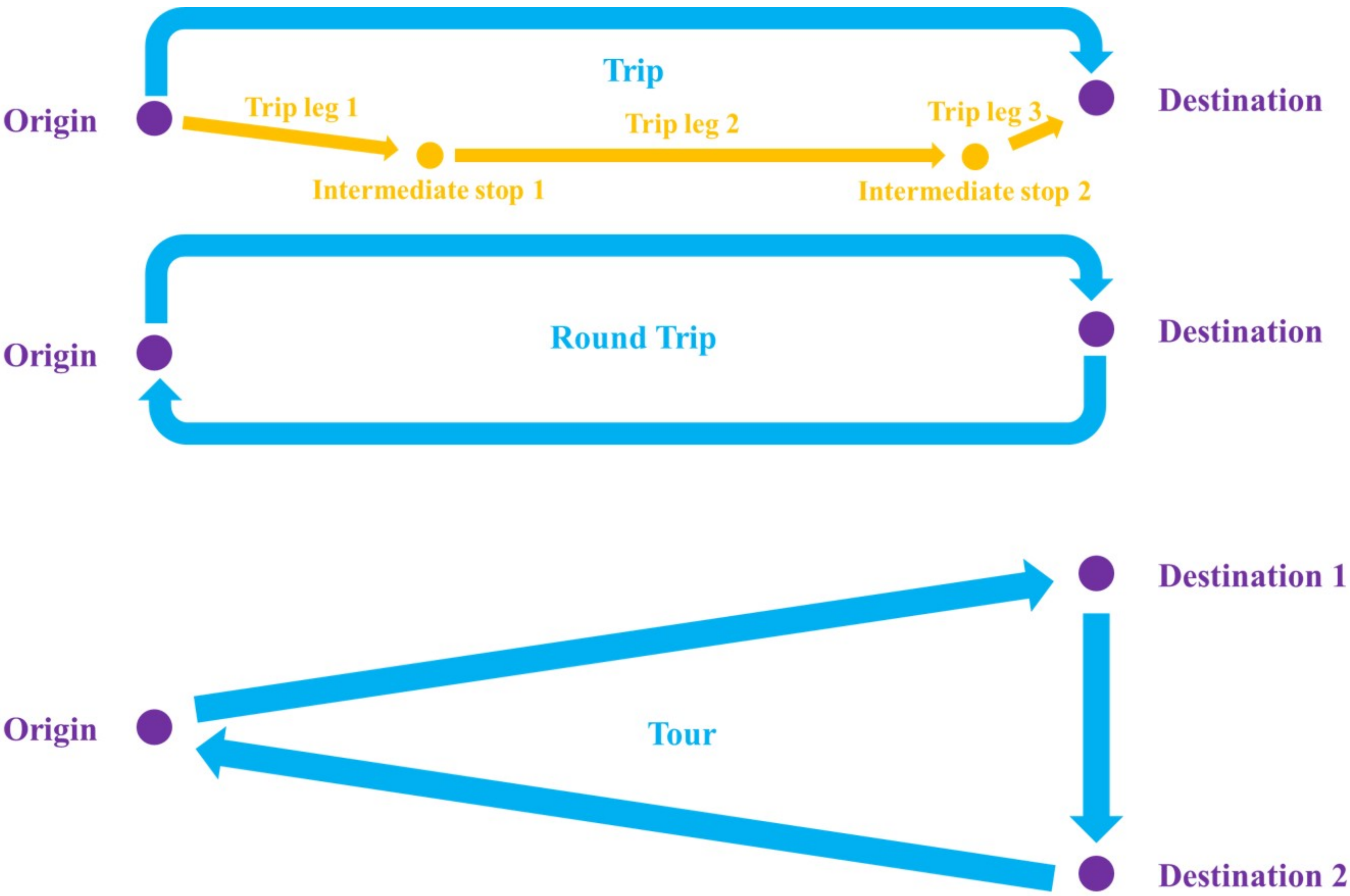


Figure 6.1 – Intermodal trip elements scheme

dividual can benefit from an intermodal transfer time to buy a snack, thus adding a specific activity transforming an intermodal trip into a tour, while it should still be considered as an intermodal trip because grocery shopping is an opportunity activity here and not a proper trip-generating activity. Figure 6.1 graphically displays these definitions. With these, intermodality characterizes trips where trip legs can be observed. This dissertation focuses on the study of home-work trips in order to observe repeated patterns and choices made by individuals who have an advanced knowledge of the mobility network to reduce the set of individuals with less alternatives because of a lack of information.

The use of several modes implies defining what a mobility or transport mode is. Traditionally, a mode characterizes the transport vehicle or mobility service used to travel. The usual ones are the walk, PT and car modes. But these general modes can often be dispatched among other sub-modes: PT can be divided among the public transport type, whether it is a light rail, a heavy rail or a bus, and the car mode can be divided according to the type of vehicle, whether it is a SUV, a large car or a small car for example. Intermodality happens when several trip legs appear and when there is a mode shift between these trips legs. The distinction is more complicated when dealing with the walk mode where there seems to be a distinction between short access trip legs and longer more physically intensive trip legs, with an unclear frontier depending on the individual's physical condition and walk-friendliness. This observation is all the more important than combining a long walk mode with another non-walk mode would be perceived as an intermodal trip from an individual's perspective. This statement also raises the issue of dealing with combination of short walk trips with another mode. Even though these display a mode combination, it is assumed that a walk access is required for almost every mode and that as such, the short walk mode is considered marginal and is not considered as an independent mode characterizing intermodal trips.

The modes considered in this chapter are car, PT, walk, cycle, and other. The public transport mode is considered as a whole because it is managed by a same entity and as most of the time, tickets or subscription enable accessing any public transport sub-mode in the Paris region. The other mode encompasses several other modes such as boards, taxi or interurban transport modes.

The mode change is a critical phase within intermodal trips. It is also considered as the main obstacle toward the diffusion of the intermodal mode choice alternative. Indeed, at the opposite of traditional modes, intermodal trips have additional mode transfers costs. These costs are mostly temporal but can be monetary too. They are badly perceived by the travellers because they involve the costs of leaving a mode, additional waiting time and boarding a new mode. So an intermodal trip is not only the division of a trip among trip legs with different modes, it also has important transfer characteristics. The location where this transfer happens can be called an “intermodal transfer place”.

A summary definition encompassing all of these observations would be: Metropolitan intermodality is a travelling practice involving several mobility modes within the same trip. This trip is made of trip legs connecting the origin, the destination and intermodal transfer places. The trip legs are made with different transport modes. Traditionally, an intermodal trip encompasses at least an individual motorized mode and a public transport mode but this definition can evolve by reconsidering the walk access mode and when differentiating public transport sub-modes. Before studying this phenomenon, it is fundamental to recall its used definition and the modes and mode combinations considered because they highly impact the results of the analysis.

Now that intermodal trips are defined, it is important to distinguish between multimodal and intermodal individuals, with regard to the home-work trips. A multimodal individual is an individual who chooses different transport modes to make the home-work trip, while an intermodal individual chooses an intermodal combination. Multimodality can be considered as similar to intermodality but with the use of several modes over several trips – going to work with public transit and coming back home with a car sharing service for example –, while intermodality specifically happens when several modes occur within a single trip.

6.1.2 Literature of intermodality characterization

The literature on both intermodality and multimodality uses is scarce, especially concerning metropolitan intermodality demand. Indeed, the interurban freight intermodality is much more studied and some books can be found on this topic such as Crainic & Kim (2007), especially within the framework of logistics optimization and intermodal logistics platforms. The lack of metropolitan intermodality literature probably comes from its marginal representation within the current modal mix, and from the late development and study of intermediate mobility solutions. It must also be noted that intermodality literature is not always available in English such as Massot (1999); Lichere & Foulon (1999); Richer et al. (2016) and a significant part of the literature review in Oostendorp & Gebhardt (2018), limiting its international diffusion. This observation is paradoxical because the term intermodality is often used in local urban and mobility planning to encourage the development of intermodal PT stations. Some of the few papers describing the phenomenon are presented to identify repeated patterns.

Massot (1999) does not really address the intermodality phenomenon but the wider urban multimodality phenomenon encompassing the aforementioned. The study focuses on French urban areas over 300,000 inhabitants versus the Paris region and over all of the trips made. Overall, the population is well equipped with about 78% car holding and 80% driving license holding. The individuals are spread out among 30% exclusive car users, 14% exclusive PT users, 3% neither using a car nor PT, leaving about 53% multimodal individuals. It distinguishes a strong spatial and public transit network density effects because this figure goes up to 64% multimodal individuals in the inner city of Paris. The multimodal individuals mostly are PT dominant users with irregular car use in the Paris region while they mostly are car users with irregular PT use in other French urban areas. In both cases, the multimodal users make significantly more monthly trips than the average population. In the Paris urban area, multimodal trips more generally happen with an origin or destination in the city centre. To sum up, intermodal individuals are included within the multimodal individuals group, highly influenced by spatial and trip motive characteristics. This study is not extensive on intermodality but provides a first picture of the phenomenon.

A more detailed approach is displayed in Lichere & Foulon (1999). The report proposes to address intermodality defined as trips mixing individual vehicle use and PT trip legs. The study deals with data from Lyon and Marseilles to analyse general intermodality descriptors. The surveys have enabled to identify main themes and indicators related to intermodality uses. Intermodality mode choice criteria encompass parking difficulties at the destination, time and monetary savings, driving conditions. The result of the choice of intermodal transfer place is often the closest metro station from home, the station minimizing car driving time, and is related to the parking space availability at the transfer place. The activities related to intermodality are most often the daily commute to work or to studies. Results seem to indicate that women are slightly more likely to make intermodal trips, and that intermodal trips are often radial, connecting the suburb to the city centre, with a destination often located less than 500m away from a metro station. Three levels are used to characterize intermodality: the trip level, the individual level, and the geographical network level. The contribution of this study is significant because it covers a large set of indicators and gives an overview of potential intermodality drivers.

More recently, Richer et al. (2016) uses another definition of intermodality considering different PT sub-modes. For instance, this study would consider a bus and metro combination as a PTxPT intermodal trip. The perimeter is general and encompasses several French urban areas excluding the Paris region. The paper emphasizes that the intermodality concept is still not well understood and that it is best studied with passenger travel survey data. It also highlights the contradiction between the concept of systemic intermodality as a way to make mobility networks more efficient and the concept of individual intermodality highly penalized by strong mode transfer costs. It confirms that urban intermodality is more chosen for home-work or home-studies trips, by active individuals or students. Considering Richer's definition of intermodality, the trip share is around 10% for urban areas with important PT networks, with heavy growth rate of about 35% between the 1990s and the 2000s. With this intermodality definition, 75% of the intermodal trips are PT and PT combinations, making a previous individual vehicle and PT combination more marginal. The paper concludes on the importance to reconsider the walking trip legs within the intermodality framework as it could be integrated in the intermodality definition because many intermodal and multimodal users are also more likely to walk. The importance of the intermodality definition is well exposed when considering all of these studies as there clearly is a lack of common ground to enable better comparisons, and because the definition has a direct impact on the intermodal trips share. Despite that, the intermodal population seems to keep the same characteristics, with strong activity and spatial characterizations.

After these French illustrative cases, a German one is presented in Gebhardt et al. (2016); Oostendorp & Gebhardt (2018) on Berlin 2016 data collected from a dedicated survey. This paper also considers combination of PT sub-modes as intermodal trips, so about 10% of the trips are intermodal in Berlin, of which 80% are combinations of PT sub-modes. The analysis is conducted from a user perspective to determine what are the drivers to practice intermodality for an individual. It is dispatched among a first intermodal trips composition, a second spatial approach, a third trip purpose, a fourth intermodal motives, and a fifth interchange points characterization approaches. The results show the importance of new car sharing mobility services on intermodal uses because the car and PT combination is more often made with car-sharing rather than without. This combination is also more likely to be made by individuals living in decentralized neighbourhoods. The daily intermodal uses characterize better home-work and home-studies trips, but a high share of leisure and shopping trips are made with less than daily intermodal uses. The main reasons identified for making intermodal trips are again the travel time, the access to a main transport mode, the few changes required and the flexible use for the car and PT combination. The paper clearly states that PT is the central mode in intermodal trips with barriers from mode change, especially parking availability. The authors share the observation of a lack of literature on the intermodality phenomenon.

To sum up, the few studies on intermodality have different definitions of intermodality, and different ways of characterizing its trip characteristics, its users and its uses. Nevertheless, it seems to be related to main indicators of PT accessibility and network development, to active individuals and students when making their home-work and home-studies trips, and to do long-distance radial trips connecting the down-town to the suburbs. Intermodality seems to be built around the structural role of PT networks. A framework must be developed to better understand the phenomenon and to address its description, and more research is expected on this topic before building a consistent general theory.

6.1.3 Integrating intermodality in travel demand models

After this description of the intermodality demand literature, the question of how intermodality is made is an important element for understanding future mobility equilibria. Modelling gives additional information on the effects of different socio-economic, geographic and physical variables and helps comparing their explanatory power. This is a key first step before forecasting evolutions in the Paris region. But intermodality is a challenge for traditional mobility models built around forecasting monomodal car and PT trips described in Chapter 2, and the whole modelling process must be adapted to account for this phenomenon. On this task, a lot remains to do because the literature is even scarcer than for overall intermodality assessments. In order to identify and provide an answer to this intermodality modelling challenge, this subsection displays a review of the few intermodality modelling papers found before addressing the issue of the analysis unit, of the joint mode choice and assignment, of the route choice and of the phenomenon size in turn.

According to Lichere & Foulon (1999), most of the applied models represent intermodality by manually drawing attraction areas around intermodal transfer places. Even though operational, these methods do not enable to run forecasts or to get better understandings of the phenomenon because they are just a static reproduction of the observed behaviours. While the modal competition is well represented in traditional discrete choice models, the modal structure is still not clear and the intermodal combination of car and PT is often only represented as a PT sub-mode with different access speed values. They also heavily lack of parking constraints representations, individualized pricing and intermodal place characterization. The modal captivity when individuals have a limited mobility mode universe is also not well integrated, and road and PT networks are too often built separately, without common nodes to enable intermodality. Hopefully since the 1990s, things have evolved and the different spatial networks can now communicate, but most of the elements pointed out are still valid. Especially the parking constraints which are hard to deal with because of a lack of data.

Except for this report, no papers have been found on intermodality demand modelling by the author of this manuscript. Most of the existing literature rather focuses on the multimodal routing issue. The route choice on a network theory is well established and structured in Leurent (2006) which shows the mathematical foundations of graph theories and traffic assignment. The issue of dealing with a multimodal network has arisen early with Florian (1977). But this early approach only considered a car against PT route choice, within a multimodal route choice universe and not an intermodal mode choice. Boile et al. (1995); Ziliaskopoulos & Wardell (2000) developed an intermodal representation from a dynamic perspective. These latter approaches consider intermodality as an option when the road network deteriorates, with the opportunity to switch to PT as a backup solution. This is an opportunistic behaviour representation rather than a true intermodal behaviour, and it is more related to routing under network disruptions such as in Pronello et al. (2017). It considers intermodality as a PT network access when the car network is facing a disruption, only including the PT route choice at the closest PT station on the road network, which quite limits the intermodality phenomenon approach. A key element to account for in this intermodality assignment modelling is the individual choice against other monomodal alternatives, which must put forward some advantages for the individuals, whether in travel time, cost, comfort, or versatility of possible routes.

There is still much to do to well model intermodality. A first questioning should be based on the analysis unit. When modelling intermodality within travel demand models, is the final object to model a trip, a tour or individuals? This question may seem naïve but it shows that there are several different ways to represent intermodality. A solution could be to model intermodal individuals and then to consider that these have an intermodal alternative in their choice set. Another more practical one would be to model an intermodal trip choice for every individual based on variables including individual characteristics and a last solution would be to model it as a tour associated to an activity. While the first individual model option is quickly ruled out because it involves combining two models, greatly deteriorating the model results and making understanding its parameters more difficult, the other options are more similar. Valiquette & Morency (2010) states that traditional models have evolved from representing trips to activity tours. The main advantage of tours is that they include the burden of the first mode choice over the whole loop while a trip approach does not carry the first mode choice availability constraint to the trip destination. Tours enable having an overall approach of a trip within an activity framework while trips are too isolated. Studying intermodality at the tour level seems to be the most logical solution.

Another issue when dealing with intermodality is that it does not well fit the basic four step model structure. While in the basic structure, the mode choice is followed by an assignment procedure often based on travel time minimization, the intermodal modelling is more complicated. Even though some models propose to jointly model different steps such as Florian & Nguyen (1978), this is not sufficient to deal with intermodal trips. Indeed, in the mode choice step, the intermodal travel times are usually not available and must be computed as set-up OD matrices do not exist for intermodality. So here, instead of having a succession of mode choice and route choice, both are done simultaneously. They are all the more complicated that several intermodal combinations are considered, increasing the set of alternative of the mode choice at the same time.

Within this process, the computation of intermodal travel times is not so easy too. Indeed, these trips integrate an intermodal transfer place choice which is key. If the transfer place is close to the destination or to the origin, the computed travel time is almost identical to a monomodal travel time. Instead of just minimizing the travel time, some constraints or another step must be added to determine the transfer place choice. In addition to this, instead of running one standard monomodal travel time computation, several computations must be conducted between each intermodal transfer place and on different modal networks, highly increasing the travel time computation.

Aside this complexity, another main issue remains: there are less than 2% intermodal individuals in the Paris region. Statistical models are not known for being efficient on statistical margins, so specific sub-populations with a high intermodal sub-population share should probably be tested first. It must also be noticed that there usually are no intermodal solutions in route planning applications. These applications are widely used for route choice and induce many mode choices. As long as these do not widely propose intermodal trips, it is likely that intermodality will not diffuse that much, so looking at these for modelling mobility evolutions would probably be also an important factor.

In order to consider the intermodality modelling issues and with the understanding of the intermodal population in the second section, the following hypotheses are made to model intermodality:

- The study population is restricted to the active adults living in one individual households who made at least one home-work trip,
- The model is static and focuses on main observed home-work trip mode choice, so within an activity mode choice modelling framework,
- The intermodal trips considered in the EGT 2010 travel survey are the PT trips with at least one access or egress car mode to enable intermodal travel time estimation and because it represents almost every metropolitan intermodal combination.

The model presented in the third section does not answer all of the modelling issues, but it is a first step toward a better integration of the intermodality phenomenon within metropolitan mobility demand models.

6.2 Phenomenon Characterization: Application to Paris

This section is dedicated to the statistical description of metropolitan intermodality in the Paris region. The data set used is the Paris region passenger travel survey EGT 2010 used in the previous chapters. Passenger travel surveys data is efficient for studying intermodality because it enables addressing the phenomenon from several perspectives, by crossing socio-economic and trip information, the main drawback being the year of the survey which is a little old for studying this evolving phenomenon. For each population analysis, metropolitan intermodality is addressed from a succession of individual, trip and trip leg perspectives. Within these perspectives, a comparison of a general analysis of the phenomenon in the Paris region with four populations used in the previous chapters is made. The population of active one individual households making home-work trips well fits the analysis as former studies have shown that intermodal trips are more often made by active individuals for their home-work trips.

6.2.1 Phenomenon identification and magnitude

All the figures displayed in this chapter come from a statistical processing of the EGT 2010 survey with R and Microsoft Excel software. A summary of these statistics is available in Appendix C. It is important to bear in mind that the analyses are tightly linked to the available data and to the way it is coded within the EGT 2010 files.

An illustration of this appears when dealing with the number of trip legs within trips. Indeed, Table 6.1 shows trip mode shares of the Paris region by the number of trip legs. Without additional processing, there is no trip with 2 trip legs, they all equal 1 or above 2. This observation comes from the way trips are recorded within the EGT 2010: Each walk only trip is coded with one walk trip leg, while for every other mode, additional walk access and egress trip legs are generated with a standard 60 meters value when not recorded. The reason for this coding is unknown to the author, but it complicates the identification of intermodal trips. As could be expected, most of the trips (88.6%) are simple, with less than 4 trip legs. The main trip mode is established as the heaviest mode used within a trip.

The heaviest mode is considered to be the public transport so any trip encompassing public transport is assigned a PT main trip mode. A combination of several PT modes, or even several PT metro lines is counted several times with this indicator. The data seems to validate the intuitive thinking that PT is a key element of intermodal trips with trip legs number above 3.

Number of trip legs per trip	Paris region trip share	Number of observations	Paris region main trip mode share					
			Walk	Bike	Motorcycle	Car	PT	Other
1	38.7%	45,543	99.9%	0.0%	0.0%	0.0%	0.0%	0.0%
3	49.9%	65,373	0.0%	3.2%	2.8%	75.5%	17.8%	0.8%
4	5.9%	6,529	0.0%	0.0%	0.1%	1.0%	98.5%	0.4%
5	3.6%	4,278	0.0%	0.0%	0.0%	0.3%	99.6%	0.1%
6	1.3%	1,761	0.0%	0.0%	0.0%	0.0%	100%	0.0%
7 and over	0.6%	778	0.0%	0.0%	0.0%	0.0%	100%	0.0%
Total	**100%**	**124,262**	**38.7%**	**1.6%**	**1.4%**	**37.8%**	**20.2%**	**0.4%**

Table 6.1 – Trip legs and main trip mode shares in the Paris region

In order to avoid the issue of the number of trip legs to identify intermodal trips, a processing is made to exclude every walk trip leg from the trip leg count. Indeed, the access, egress and transfer walk trip legs are not relevant for qualifying intermodal trips. The other long walk trip legs are neglected because their number is small with more than 96% walk trip legs under 1km. Another correction is added to avoid counting public transit trip legs combinations. The results appear in Table 6.2 with an indicator enabling to differentiate intermodal trips. The share of intermodal trips is estimated at about 1.8%, or 11.4% when considering PT combinations, which is consistent with previous studies evaluating the share of intermodal trips at about 10-15% in big cities with developed PT systems. As can be seen in the table, these intermodal trips are almost all (94.0%) made with a main recorded mode being the public transport. The 4.0% share of intermodal trips made with the car as the main mode mostly are combinations of cars and interurban trips such as for a trip involving a car before taking a plane which are not metropolitan trips. The other main modes are probably similar with a taxi and interurban mode combination. Based on these observations and because the aim of public authorities for developing intermodality is to support PT use and not individual vehicle intermodality, the remaining part of this chapter only considers main PT mode intermodal trips. With this definition, 8.4% of the PT trips are intermodal trips.

So with a definition of intermodality based on the use of public transit within a

Number of non-walk trip legs per trip	Paris region trip share	Number of observations	Paris region main trip mode share					
			Walk	Bike	Motorcycle	Car	PT	Other
Not intermodal	98.2%	121,805	39.4%	1.6%	1.4%	38.4%	18.8%	0.4%
Intermodal	1.8%	2,457	0.0%	0.1%	0.4%	4.0%	94.1%	1.5%
Total	**100%**	**124,262**	**38.7%**	**1.6%**	**1.4%**	**37.8%**	**20.2%**	**0.4%**

Table 6.2 – Intermodal trips and shares of trips by main mode in the Paris region

trip while neglecting public transit only combinations because of the easiness to switch between PT sub-modes in the Paris region, intermodal trips can be identified within the EGT 2010 dataset. Once they are identified, it is possible to characterize intermodal individuals as individuals who made at least one intermodal trip, intermodal trips and intermodal trip legs belonging to an intermodal trip.

6.2.2 Individual perspective

The few available literature on intermodal trip makers has enabled to identify a few emerging characteristics of this population: they seem to be active individuals leaving close to PT connections. A description of the intermodal Paris region population in comparison with the general population is proposed next, with descriptors including several individual and household geographic and socio-economic variables. A second comparison within the study population of active adults in one individual households is also proposed and used to identify potential explanatory variables for the model developed in the fourth section. In this subsection, demographic, socio-economic, residential location and mobility tools availability, and trip indicators are investigated in turn.

6.2.2.1 Demographic indicators

Starting with individual demographic variables, it seems that the age, gender and declared mobility disability influence intermodality uses. Indeed, the age is an important intermodality factor but does not have a linear impact on intermodality choice as exposed in Figure 6.2. Even though the average age of intermodal adults is lower than for the overall Paris region population – 42.1 against 46.2 – this observation does not stand for the study population where both average ages are roughly the same. A better understanding is possible when looking at age groups: when the shares are not much different for the younger population from 18 to 34, the share of the older population over 64 highly diminishes from Paris region adults to intermodal adults, while the share of 35 to 54 adults is much more important in the intermodal population. Regarding the study population, the age group shares are similar between intermodal adults and the overall study population but this can be explained because individuals over 64 often are not active any more, so are automatically excluded from the study population. So intermodal users are younger than the rest of the Paris region population, but this comes from the lack of aged intermodal users. The main age group represented within intermodal users is the 35 to 54 group, so individuals which are more likely to be active individuals than average. This is confirmed because within the study population made only of active individuals, the difference between intermodal users and the overall study population is less important.

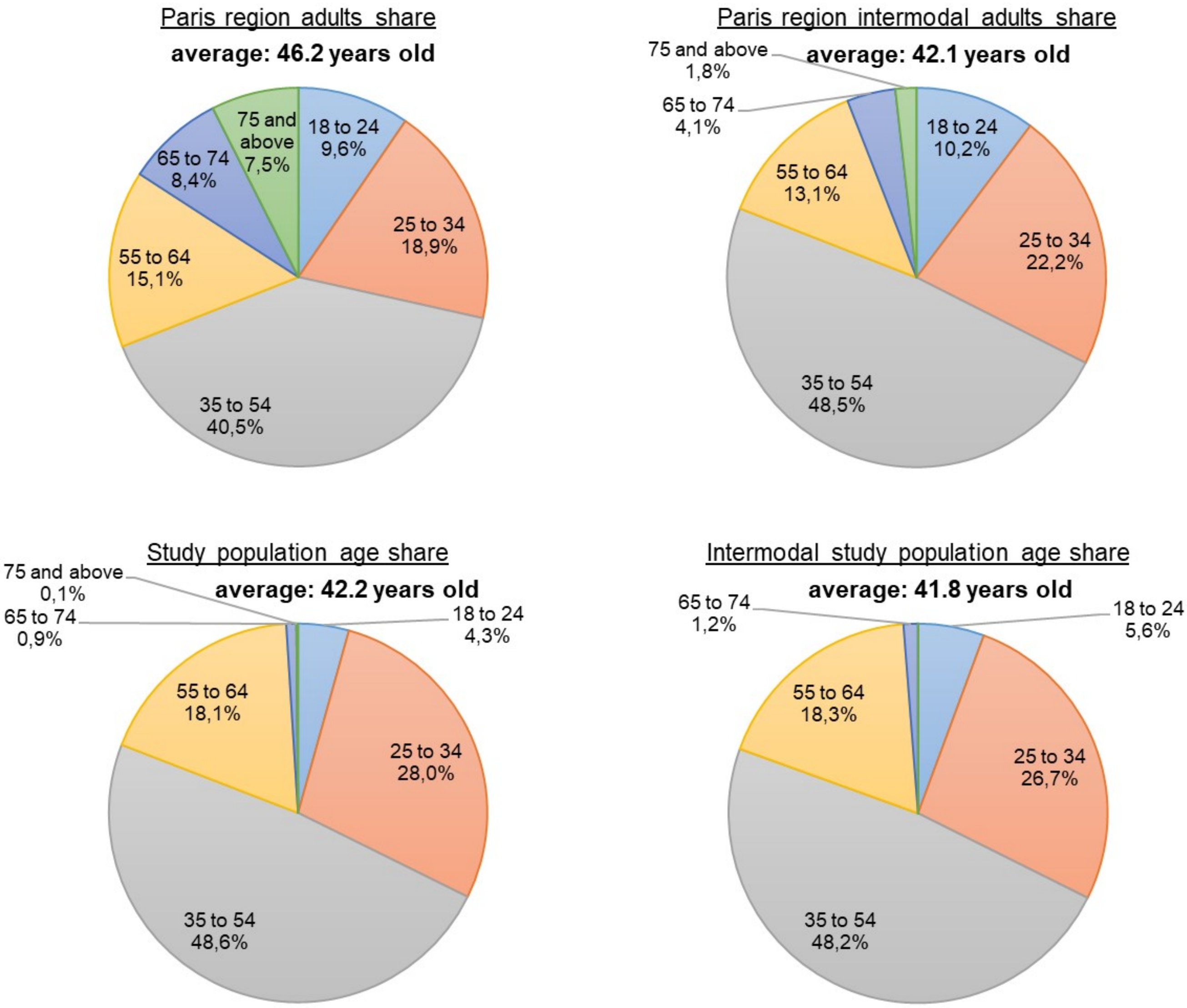


Figure 6.2 – Age shares for the four populations

The effect of gender requires interpreting because it is counter-intuitive. When there are more adult women in the Paris region with a 53.1% share[1], the share of women in the intermodal adult population is even a bit higher at 53.9% in Figure 6.3. When looking at the study population, there are more men in this population at 53.0%, and within the intermodal study population, there are more women at 52.3%. So the observation for the study population is that women are more likely to be intermodal than men, which is mirroring the general population. It seems that the criteria of the study population are interacting with the gender variable and women out of the study population are probably less intermodal.

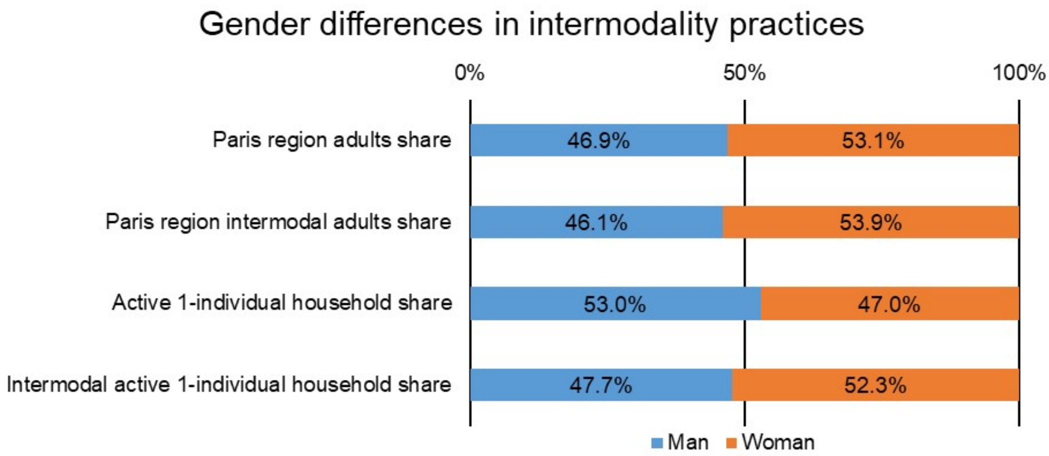


Figure 6.3 – Gender shares for the four populations

To conclude with fixed descriptors of individuals, it is important to consider individual mobility. Whether some individuals have mobility disabilities is key for assessing their mobility behaviour. Sometimes, mobility disabilities can be overcome with adapted technical solutions. But as intermodality requires to use a modal chain involving several modes with different accessibility and requiring different adaptations from a mobility disabled individual, mobility disabled individuals are expected to be less intermodal. Confirming this reasoning, the share of self-declared intermodal mobility disabled individual is low: 5.4% against 9.2% for the general population, and less with 5.9% against 6.1% for the study population which is younger and more physically able.

[1]the 53.1% share may seem important, but one should bear in mind that the women life expectancy is higher. So even if there are about 50% rate in most younger age groups, this is not the case any more for older age groups. I can explain the overall higher share of women

6.2.2.2 Socio-economic indicators

After displaying the importance of these demographic variables in intermodality users, socio-economic descriptors are studied. A bridge between these two categories is the number of daily trips made by an individual because it is both influenced by individual conditions and by socio-economic characteristics. Intermodal individuals would be expected to be more versatile and to have more mode choice options, with a higher mobility need than others. At the same time, intermodal trips imply the use of several modes, so moving over longer distances. It induces that they make less trips because these are more burdensome. It is verified with the average number of daily trips dropping from 4.0 for the general and study population to 3.9 and 3.7 for intermodal adults and for intermodal adults in the study population. The number of daily trips and intermodal users seem to have opposite trends.

A standard socio-economic indicator describing individuals is the education level. Figure 6.4 displays the highest level of education reached by individuals, and enables comparison among the general, study and intermodal populations. The results are straightforward: the study population made of active individuals is more educated than the average population with more than 65% reaching a higher education level against less than 48% on average. This gap is almost wider between general and study populations and intermodal users with about 76% of the intermodal study population having a higher education level. While the number of high school degree levels is quite stable, it mostly is the share of education levels under high school degrees that is under represented among intermodal users. So intermodality is mostly chosen by individuals with a medium to high level of education while individuals with a low level of education seem to be excluded from intermodality. This goes against considering intermodality as a constraint for individuals who are not able to chose other alternatives.

When looking at the occupations on Figure 6.5, the same observation as in the literature can be made: intermodal adults mostly are active individuals for more than 75% of them. This is understandable because this population has strong mobility constraints and large mobility needs, and also because it has larger mobility tools portfolios. It is also consistent with the previous statement about the age effect on intermodality, as the 35 to 54 age group has many active adults compared with other age groups. This justifies the interest of studying intermodality within a study population made of active individuals. The students are also well represented within intermodal adults compared to the general population, because

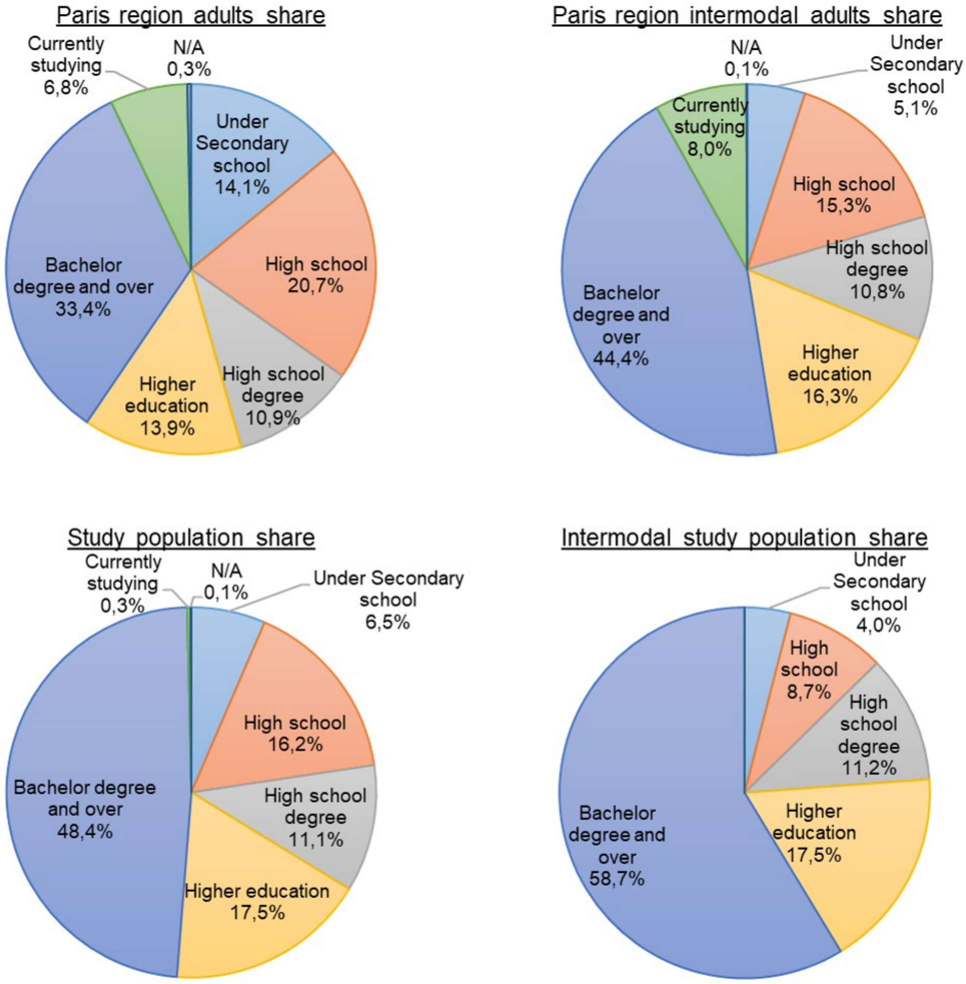


Figure 6.4 – Education group shares for the four populations

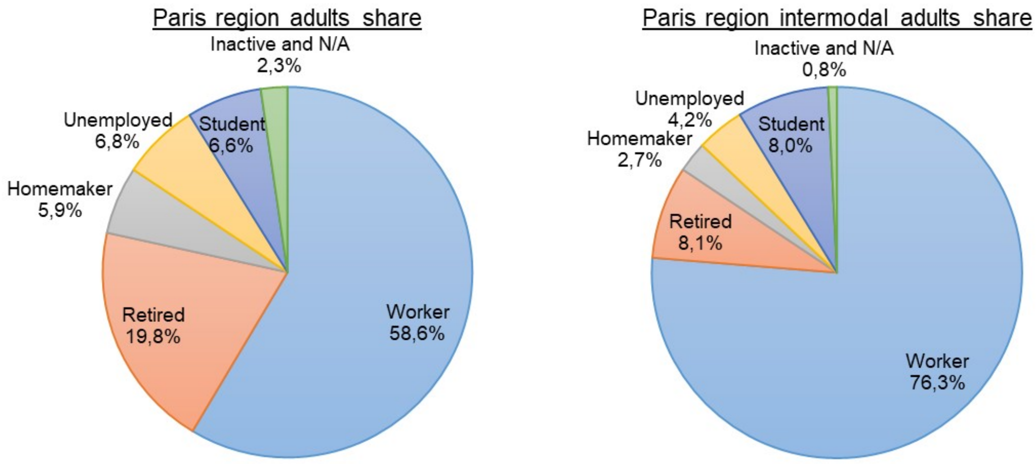


Figure 6.5 – Occupation shares for two populations

their constraints are similar to active individuals even though they often are less wealthy and cannot afford to withhold too many mobility tools. A quick look at the socio-professional categories of intermodal active individuals in Appendix C enables to state that these mostly are executive, intellectual and intermediate professions rather than blue-collar workers or employees for both the general and the study population. This is consistent with the previous observation that intermodal individuals are more educated than the average population. The workplace location variable also indicates a high centralization of workplaces in the agglomeration – more than 79% of the active individuals work in the agglomeration in the Paris region –, and more specifically in the agglomeration centre and in urbanized agglomeration communes for 83% of intermodal users. In addition to supporting the previous analysis that intermodal users are skilled workers, the fact that skilled jobs are more centralized in Paris and its immediate surroundings indicates that intermodality is more used to access these central areas which are well connected to the PT network.

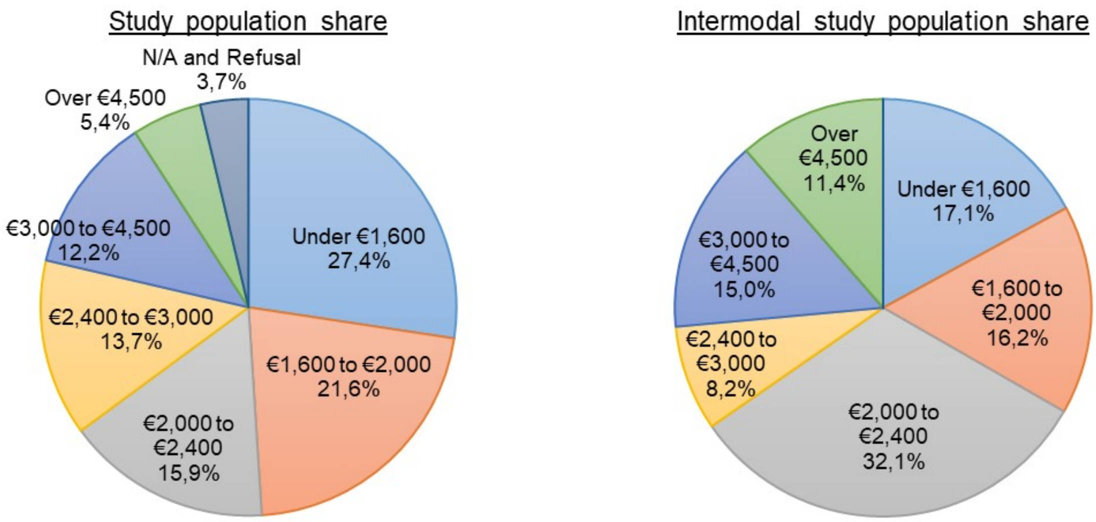


Figure 6.6 – Income shares for two populations

The socio-economic characteristics of these individuals tell much information on the intermodal population. But one main variable is not available at the individual level in the EGT 2010: the income. In order to study its effect, it is necessary to assess it at the household scale. Even though limiting when dealing with populated households, it is easier to deal with for the study population made of one individual households where the household income equals the individual income. Figure 6.6 first shows a high share increase for the richer intermodal study population groups above EUR 3,000 per month following the previous observation.

There is also an effect for the EUR 2,000 to EUR 2,400 per month category which increases its share for intermodal users while the shares of all of the other income group decrease. This effect is difficult to analyse but it is nonetheless important to note that more than half of the study population earns less than EUR 2,000 while it is less than a third for the intermodal study population. Even though this income effect is not straightforward for incomes around the median, it is clear that low-income households are less likely to be intermodal while it is the opposite for high-income households of the study population.

6.2.2.3 Residential location and Mobility tools holding indicators

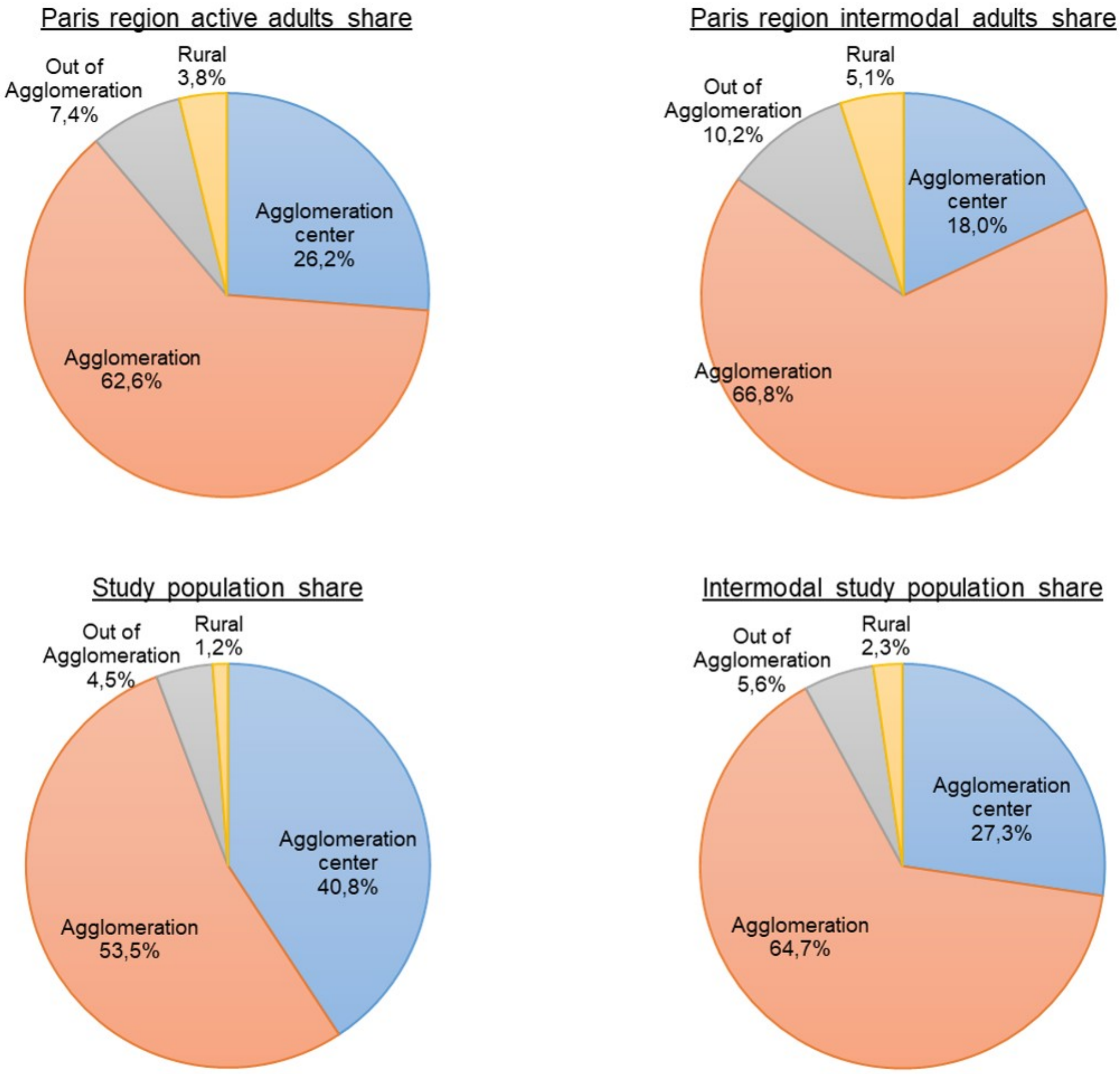


Figure 6.7 – Geographical location for the four populations

To continue with household level variables, the household location is an indicator of socio-economic and geographical characteristics. Figure 6.7 shows that intermodal users rather are located out of the agglomeration centre because all of the other commune types are more represented within the intermodal population than in the general population. This stands for the study population too even if it is more concentrated in the agglomeration centre than the general population. This trend is confirmed by the household location type: intermodal individuals have a higher share – 47.9% against 30.8% for the general population and 24.2% against 10.5% for the study population – of individual housing generally located in the suburbs than the general population. Interpreting this result with the fact that workplace locations are more often located within the agglomeration and the agglomeration centre suggests that intermodal trips may be radial connections between the suburbs and the agglomeration centre or areas close to it. This observation fits with the intuition that intermodal trips should probably begin in areas not so well connected to the PT network, requiring a first trip leg to access it. Then the end of the PT trip should be close to the destination to avoid the burden of using another mode than walk for the last trip leg.

	Paris region active adults share	Paris region intermodal actrive adults share	Active 1-individual household share	Intermodal active 1-individual household share
PT subscription share	38.1%	72.5%	54.2%	77.7%
Car availability in the household	75.9%	85.3%	53.8%	63.4%
Average number of cars in the household	1.1	1.4	0.6	0.7
PT subscription and car available	22.6%	61.0%	17.7%	45.5%

	Paris region adults share	Paris region intermodal adults share	Active 1-individual household share	Intermodal active 1-individual household share
Company car in the household	8.8%	8.3%	4.3%	5.9%

Table 6.3 – Mobility tools holding for the four populations

The last element to study at the individual scale is the equipment holding, which also links this chapter to the mobility tool chapters of this dissertation. It is also logical because making intermodal trips requires a personal logistic to be able to perform these trips. As expected, the PT subscription share in Table 6.3 is much higher for intermodal individuals, and also for the study population compared with the general population. Indeed, companies must contribute to at least 50% of an employee's PT subscription if used for home-work trips. The car availability is also an indicator but less important, especially for the study population. For active individuals, having a company car available in the household does not seem so important for the general population but is better represented within the intermodal study population which is not easy to explain. The most relevant point of this analysis is the analysis of the PT subscription and car availability combination, which is more represented in the intermodal population. This result was expected because the car and PT combination is a traditional intermodal combination, especially with the definition of intermodality in this chapter.

6.2.2.4 Trip and Trip leg indicators

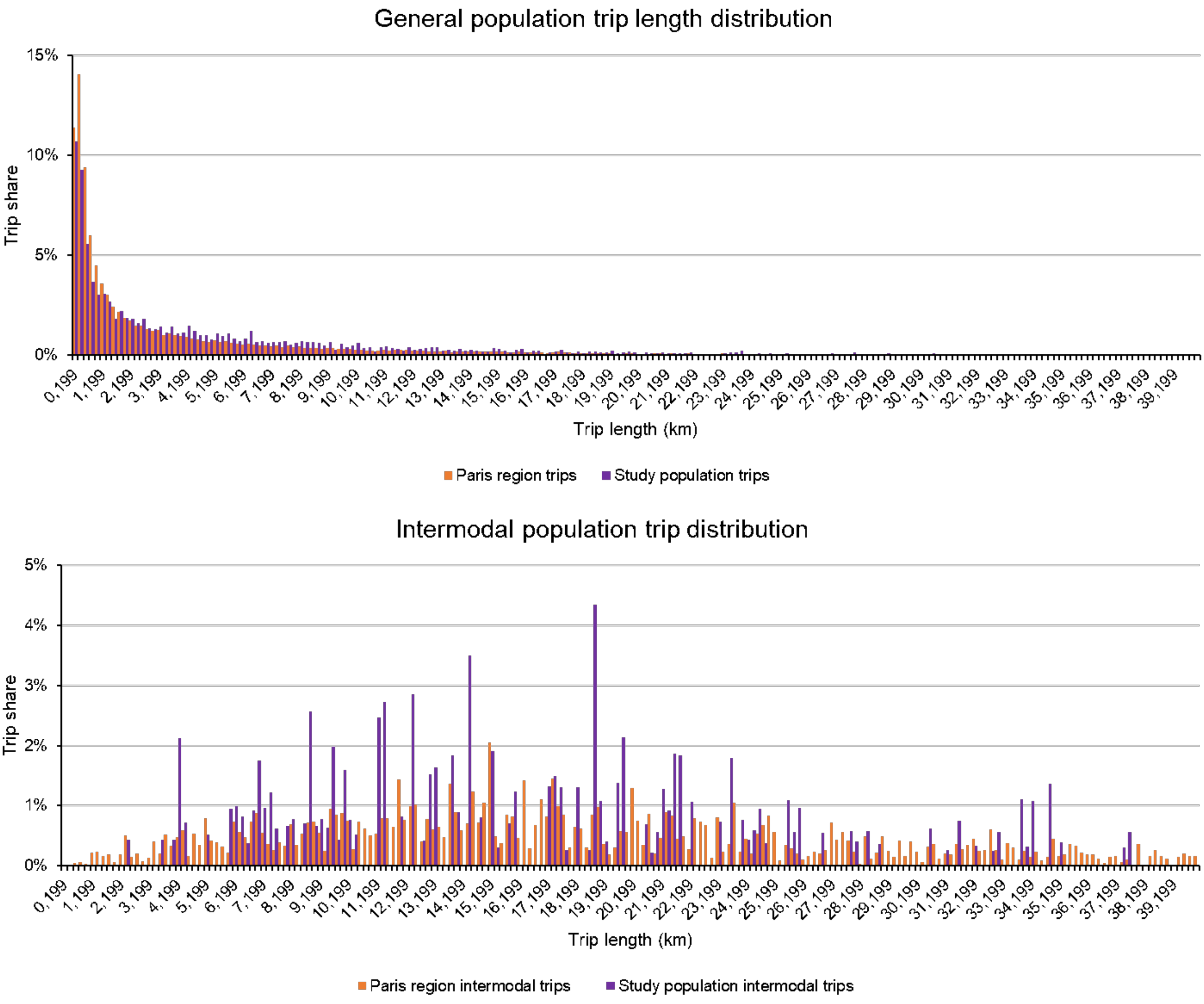


Figure 6.8 – Distribution of trip lengths for the four populations

Now that knowledge about the profile of intermodal individuals has been gathered, it is important to better understand patterns of intermodal trips. Except for the definition, these intermodal trips have specific length, duration, demand, origin-destination and geographical characteristics. They are investigated in turn.

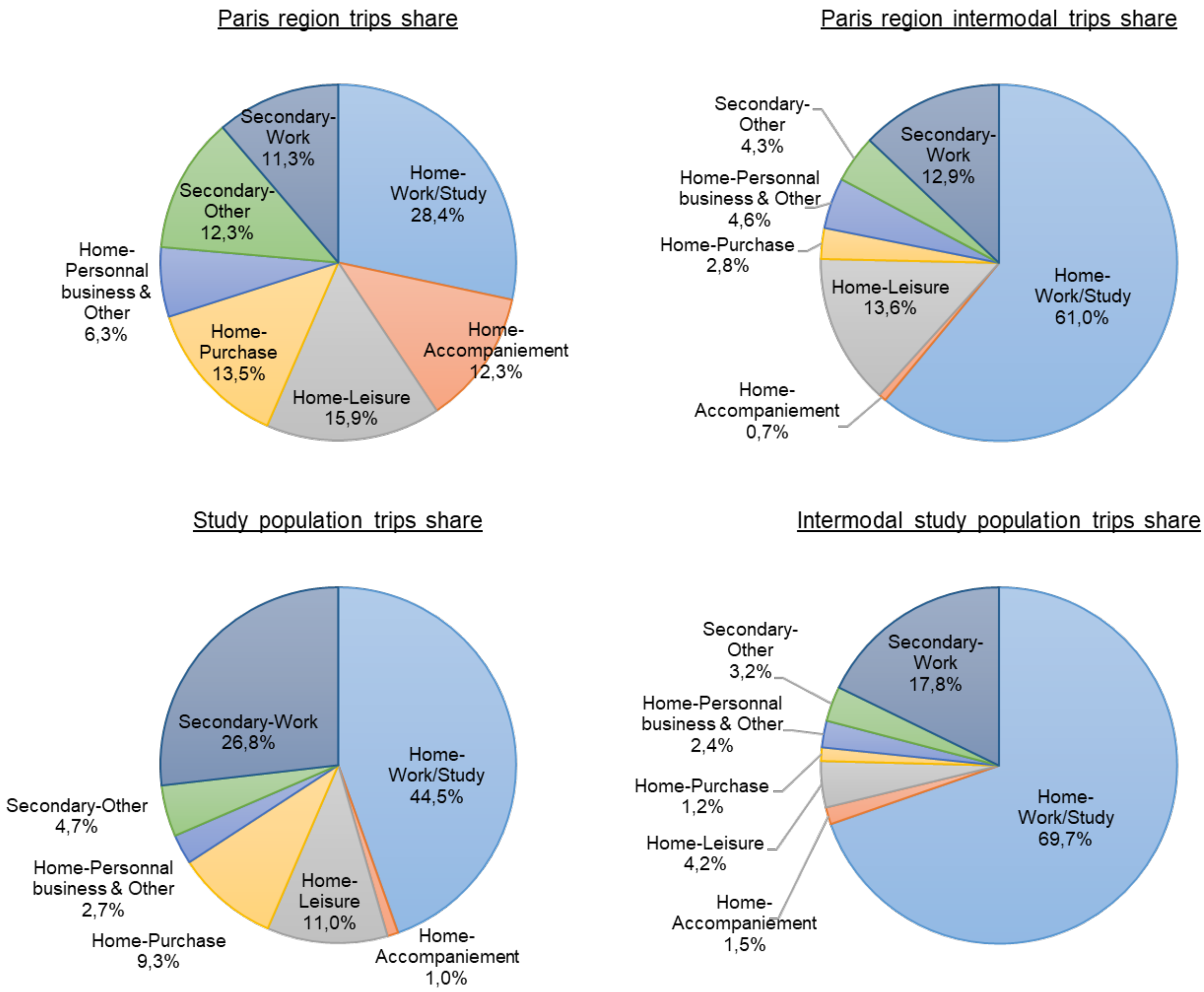


Figure 6.9 – Trip shares by trip purpose for the four populations

As can be seen from the trip length distribution displayed in Figure 6.8, the trip length distribution for the Paris region population is high for low distances and then decreases with longer distances, taking the shape of a log-normal distribution. Intermodal populations show different distribution patterns with almost no short distances and a wide spread around a high mean value. The shape is irregular but this may come from a lack of observations or too small intervals. For the general and study populations, the average trip length is around 5km while the average intermodal trip length is about 18km, which confirms these different patterns. It can easily be explained because it is burdensome to practice intermodality for short trips which are easy to walk or where the mode transfer duration is too important as opposed to the trip duration. There seems to be a value under which there are almost no intermodal trips at about 2km, with 99.0% of the intermodal trips over this threshold. The trip duration variable is not displayed because it follows the same pattern as the trip length as both are correlated. It is also less reliable because it is a self-reported value with a gathering of the values at 5 minutes step intervals while trip length are crow fly distances.

A regular pattern identified in the literature is the trip purpose effect. For the general population, the different trip purposes shown in Figure 6.9 are well spread out with home-work/study trips at a 28.4% share. But when selecting the study population, this share goes up to 44.5%, and 26.8% secondary trips[2] linked to work, which is expected considering the active study population. The share of the home-work/study intermodal trips is wider than for the general population, reaching a 69.7% intermodal trip share for the study population. This result is similar to what is found in the literature, but still pronounced here. It is all the more determinant when adding secondary trips linked to work. So intermodal trips are mostly home-work/study trips. Considering the study population, there are no home-study trips so intermodal trips are mostly home-work trips.

In order to get more details on the trip location and flows, Origin-Destination(OD) matrices from Table 6.4 can reveal general trends. To avoid round trip double count, a distinction is made between AM OD matrices with trips beginning between 12:00am and 11:59am, and PM OD matrices with trips beginning between 12:00pm and 11:59pm. When Paris region and study population trips have most of their flows – more than 70% of the trips – inside the same commune type, it is the reverse for intermodal trips which are rather connecting the agglomeration, out of agglomeration and rural communes to the agglomeration centre. For the study population, almost no intermodal trips connects out of agglomeration and rural areas among them. The AM and PM matrices are almost symmetrical suggesting that intermodal trips are probably regular flows, which would fit the observation that intermodal trips are mostly home-work trips. They show that most of the intermodal trips are issued from communes out of the agglomeration centre in the morning, fitting the observation that intermodal individuals are less living in the agglomeration centre than the overall population.

Using Transcad as a GIS software, it is possible to draw desire lines to visually

[2]Secondary trips are trips that are not linked to home. For example, leaving the office to buy some food and coming back to the office is a secondary-work trip.

Paris region trips AM

Origin Commune	Destination Commune: Agglomeration center	Agglomeration	Out of Agglomeration	Rural	N/A	
Agglomeration center	21.9%	3.7%	0.1%	0.0%	0.1%	**25.8%**
Agglomeration	8.1%	53.4%	0.8%	0.4%	0.2%	**62.9%**
Out of Agglomeration	0.4%	1.3%	5.3%	0.5%	0.1%	**7.7%**
Rural	0.2%	0.9%	0.8%	1.5%	0.1%	**3.4%**
N/A	0.0%	0.1%	0.1%	0.0%	0%	**0.2%**
	30.6%	**59.3%**	**7.2%**	**2.4%**	**0.5%**	**100%**

Paris region intermodal trips AM

Origin Commune	Destination Commune: Agglomeration center	Agglomeration	Out of Agglomeration	Rural	N/A	
Agglomeration center	3.8%	4.3%	0.7%	0.4%	1.3%	**10.5%**
Agglomeration	45.9%	17.9%	0.5%	0.2%	2.3%	**66.7%**
Out of Agglomeration	8.8%	3.6%	1.1%	0.3%	0%	**13.9%**
Rural	3.9%	2.3%	0.6%	0.6%	0%	**7.3%**
N/A	0.9%	0.3%	0.3%	0%	0%	**1.6%**
	63.2%	**28.4%**	**3.3%**	**1.5%**	**3.6%**	**100%**

Study population trips AM

Origin Commune	Destination Commune: Agglomeration center	Agglomeration	Out of Agglomeration	Rural	N/A	
Agglomeration center	31.4%	11.0%	0.2%	0.0%	0.1%	**42.7%**
Agglomeration	13.8%	36.1%	0.7%	0.4%	0.5%	**51.5%**
Out of Agglomeration	0.6%	1.4%	2.0%	0.2%	0.1%	**4.3%**
Rural	0.2%	0.5%	0.3%	0.3%	0.0%	**1.2%**
N/A	0.1%	0.1%	0.0%	0%	0%	**0.2%**
	46.2%	**49.1%**	**3.2%**	**0.9%**	**0.7%**	**100%**

Study population intermodal trips AM

Origin Commune	Destination Commune: Agglomeration center	Agglomeration	Out of Agglomeration	Rural	N/A	
Agglomeration center	4.6%	8.6%	1.6%	1.8%	1.4%	**18.0%**
Agglomeration	40.2%	12.2%	0%	0%	12.1%	**64.4%**
Out of Agglomeration	6.1%	4.7%	0%	0%	0%	**10.9%**
Rural	2.8%	0.6%	0%	0%	0%	**3.5%**
N/A	1.6%	1.6%	0%	0%	0%	**3.2%**
	55.4%	**27.7%**	**1.6%**	**1.8%**	**13.5%**	**100%**

Table 6.4 – OD AM and PM matrices for the four populations

display the intermodal trip origin and destination flows in the Paris region in Figure 6.10. Despite the high number of lines, it is possible to observe that most of the trips are radial and centralized in the agglomeration centre which corresponds to the OD flows interpretation.

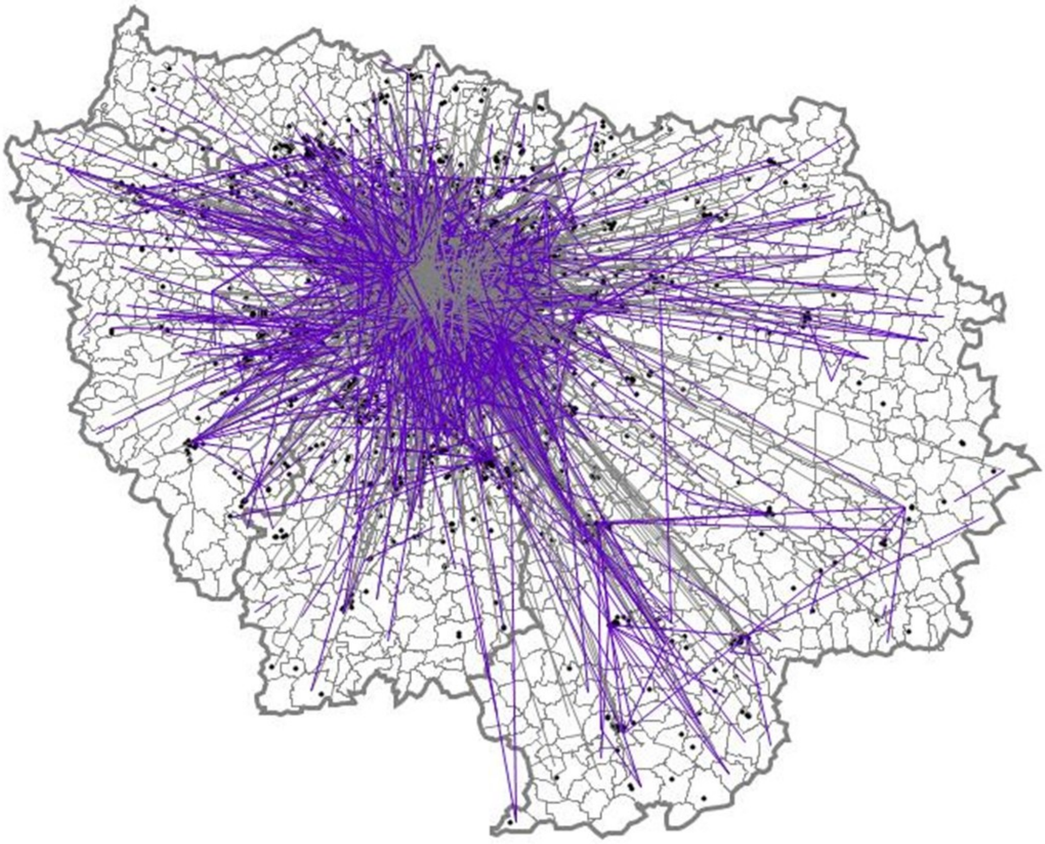


Figure 6.10 – Desire lines of intermodal trips for the Paris region

With an intermodality definition evolving around public transit use, the combinations of access and egrees modes with public transit trips are key for understanding the phenomenon. In order to get information on trips going out of home and trip coming back home, the AM and PM distinction is made again with the assumption that individuals usually leave home in the morning and come back in the afternoon and night. This distinction enables to study if there are differences between the access trip leg to the PT from home and the last egress trip from the PT stop to the destination. Indeed, an intuitive hypothesis would be that the car mode is more used to do the access from home trip and the egress trip destination work trip rather than the egress from home and access from trip destination. The first case requires keeping the car home, enabling its use for other home-based trips while the second case requires keeping the car at the final PT stop, which is less practical for other car uses. Table 6.5 shows the results of processing for the access and egress modes. The hypothesis of car uses mostly between home and the public transport stop is supported by these results, with more than 73% and 47% for the morning access trip, as opposed to less than 18% and 23% for the evening egress general and study populations. But it seems that this validation is less true for the study population. While most of the access and egress trips of the general population involve the car use – more than 80% of the trips –, the mode universe is more diverse for the study population with more than 10% of the intermodal trips involving a bike use. An important part of the intermodal trips of the study population also involves an interurban mode which is probably related to the active population filter and which is specific because these trips are not proper metropolitan trips.

After focusing on intermodal individuals and trips, it is important to try to characterize trip legs because intermodal trip legs may also display different patterns than for the general population. They can also give information on how intermodality is made, especially for route choice analysis. But this analysis is subject to the way trip legs are recorded in the EGT 2010. As exposed in the introduction of this section, it is difficult to well understand walk and PT trip legs because 60m walk trip legs are systematically generated around each non-walk mode use even without true trip leg, and because PT trip legs are created for each transit line change, even within the same PT sub-mode. These limits are lifted for the other modes where the trip leg count is less subjective. In order to draw a comparison, Table 6.6 displays the average trip leg length depending on the populations and the trip leg mode. The detailed trip leg shares by trip leg length is available in the Appendix C.

The first things that this table tells is that walk trip legs are roughly the same with relatively small changes. The length of PT trip legs increases and is almost the double of the general population for both intermodal cases. This observation is consistent with considering intermodality based on the PT mode and over long trips. The other car, motorcycle and bike trip legs are systematically shorter than average for the intermodal trip legs confirming that these mostly are access modes covering short distances to reach the main PT mode.

This section has given a detailed analysis of the intermodality phenomenon in the Paris region and for the study population. The results corroborate the few aspects found in the literature. Generally speaking, it seems that intermodality is mostly chosen by middle-aged active and educated adults in medium to high

Paris region intermodal trips

AM

Access mode	Egress mode: Walk	Taxi	Interurban	Car	Motorcycle	Bike	Other	
Walk		0.2%	3.9%	7.8%	0.1%	1.1%	0.1%	**13.2%**
Taxi	0.2%							**0.2%**
Interurban	2.7%			0.1%				**2.8%**
Car	73.1%		0.2%	0.2%				**73.5%**
Motorcycle	1.2%							**1.2%**
Bike	6.6%			0.3%		1.7%		**8.5%**
Other							0.6%	**0.6%**
	83.6%	**0.2%**	**4.2%**	**8.5%**	**0.1%**	**2.8%**	**0.7%**	**100%**

Paris region intermodal trips

PM

Access mode	Egress mode: Walk	Taxi	Interurban	Car	Motorcycle	Bike	Other	
Walk		0.6%	1.6%	60.8%	0.8%	4.7%	0.4%	**68.9%**
Taxi	0.3%							**0.3%**
Interurban	7.7%	0.1%		0.6%				**8.4%**
Car	17.8%		0.1%	0.4%		0.2%		**18.6%**
Motorcycle	0.3%							**0.3%**
Bike	1.7%			0.1%		1.1%		**2.9%**
Other	0.3%						0.4%	**0.7%**
	28.1%	**0.7%**	**1.7%**	**61.9%**	**0.8%**	**6.1%**	**0.8%**	**100%**

Study population intermodal trips

AM

Access mode	Egress mode: Walk	Taxi	Interurban	Car	Bike	Other	
Walk		1.1%	12.9%	9.6%	2.2%		**25.8%**
Taxi	1.9%						**1.9%**
Interurban	3.2%						**3.2%**
Car	47.8%		2.8%	0.6%			**51.2%**
Bike	15.0%				2.1%		**17.1%**
Other						0.9%	**0.9%**
	67.9%	**1.1%**	**15.6%**	**10.2%**	**4.3%**	**0.9%**	**100%**

Study population intermodal trips

PM

Access mode	Egress mode: Walk	Taxi	Interuran	Car	Bike	Other	
Walk		1.5%	3.0%	42.8%	8.6%		**55.8%**
Interurban	11.5%			2.0%			**13.6%**
Car	22.6%			0.4%			**23.0%**
Bike	1.7%				1.5%		**3.2%**
Other	3.1%					1.3%	**4.4%**
	38.9%	**1.5%**	**3.0%**	**45.3%**	**10.1%**	**1.3%**	**100%**

Table 6.5 – Access and egress mode shares for intermodal trips for the four populations

Average trip length (km)	Trip leg mode							
	Walk	PT	Taxi	Interurban	Car	Motorcycle	Bike	Other
Paris region trip legs	0.2	5.6	8.2	27.0	6.1	6.4	1.9	1.4
Paris region intermodal trips legs	0.2	10.6	6.9	27.6	4.0	2.8	1.4	0.8
Study population trip legs	0.3	5.4	11.2	47.8	7.8	6.1	2.3	0.9
Study population intermodal trip legs	0.2	10.2	11.3	56.0	3.7	N/A	1.5	0.8

Table 6.6 – Average trip lengths by trip mode for the four populations

income groups living out of the agglomeration centre holding a PT subscription and having an available car. The intermodal study population seems to be more feminine but the overall intermodal population of the Paris region is slightly more masculine. By definition, intermodal trips are more complex than monomodal trips and cover longer distances while almost absent from trips under 2km. Most of them are home-work/study trips, with a radial pattern connecting the jobs in the Paris agglomeration to individuals living out of the agglomeration centre. Most of the access and egress trip legs to the PT involve the car use at a point, and it seems that it is more often used between home and the PT stop rather than between the PT stop and the destination.

6.3 Intermodality Demand Modelling for a Study Population

The intermodality modelling concept and phenomenon characterization have been set up in the previous sections. The goal of this section is to build on these to create a discrete choice model representing intermodality demand for home-work trips. This model is based on an intermodality supply, demand and uses and their interaction representation. This quantitative model enables to statistically estimate mode shares based on demographic, socio-economic and geographic descriptors.

In order to get around the issue of the low mode share of intermodality, a specific study of intermodal use and home and workplace PT accessibility is first conducted to highlight a demand segment where intermodality is a competitive alternative. Then, travel costs and time effects are computed because their effect is generally significant on trip making choices. The travel times for each mode are estimated using the MODUS four step model developed at DRIEA IF, and travel costs are estimated using general assumptions. This process involves the computation of intermodal travel times, which is not as straightforward as traditional monomodal travel time computation. The mode choice model is a discrete choice model with three alternatives: car, PT and intermodal. The data set feeding this model is the Paris region travel survey EGT 2010 and the study population is the active individuals in one individual households.

The following subsections describe more in-depth the analysis and results of the segmentation based on PT accessibility, the computation of intermodal travel times is then presented before eventually building amode choice model including intermodality demand.

6.3.1 Effects of PT accessibility on intermodal uses

As identified by Leurent & Polacchini (1995), secondary trip legs are important for characterizing an intermodal trip. Because the access or egress distances are tightly linked to what Leurent calls a secondary trip mode, analysing the accessibility to the main mode can probably reveal an intermodal mode choice decision structure. As intermodality is mostly built on the PT use and because it is defined around the PT use, this translates to studying PT accessibility. Within the current modelling framework, it seems that two PT accessibility indicators are relevant: the accessibility to PT from home and the accessibility to PT to the workplace. This subsection investigates the relationship between intermodality uses and the characteristics of PT accessibility from home or to the workplace. Another aspect to consider is that every PT stop is not a proper intermodal transfer place because it requires some mode switching facilitation such as parking availability. Because these intermodal transfer places rather are implemented for heavy rail, train and tram stations, the indicator should more specifically provide a rail PT accessibility. This difference is made by distinguishing PT stops for every PT sub-mode from PT stations only related to the rail system. Following these observations, the shortest distance between home and a PT station and the shortest distance between the workplace and a PT station have been computed. This indicator is not perfect because the closest PT station may not be well connected while another nearby station may be more connected and preferred, but it still gives a relevant geographical information and is not too mathematically transformed. Based on this framework, statistical analyses of the PT, car and intermodal mode shares are conducted for the home-work trip along distances to PT stations.

In order to make these analyses, the PT accessibility must first be computed. The closest distance to a PT station from home or to work are the two PT accessibility indicators studied here for the home-work trip. But these are not available in the EGT 2010 survey, and the locations are not exactly pinpointed: the infor-

PT home-work mode choice share

Home to closest PT station distance	Workplace to closes PT station distance: Under 0.4km	0.4 to 0.6km	0.6 to 0.8km	0.8 to 1km	1 to 1.4km	1.4 to 2km	2km and over	Total
Under 0.4km	58.3%	53.6%	74.4%	34.8%	53.6%	47.7%	17.6%	**50.8%**
0.4 to 0.6km	64.2%	45.6%	57.1%	58.5%	51.8%	39.3%	32.2%	**53.2%**
0.6 to 0.8km	72.5%	49.9%	66.6%	45.9%	23.6%	50.0%	24.4%	**52.6%**
0.8 to 1km	69.6%	46.7%	74.9%	38.2%	47.9%	39.7%	33.5%	**53.9%**
1 to 1.4km	57.8%	50.2%	52.1%	49.6%	52.7%	37.2%	33.6%	**49.8%**
1.4 to 2km	62.4%	50.5%	41.8%	42.3%	56.3%	34.8%	28.3%	**46.7%**
2km and over	59.5%	39.4%	39.2%	23.8%	38.7%	23.1%	11.0%	**31.7%**
Total	**63.7%**	**48.7%**	**59.8%**	**42.7%**	**48.1%**	**38.2%**	**24.2%**	**49.1%**

Car home-work mode choice share

Home to closest PT station distance	Workplace to closes PT station distance: Under 0.4km	0.4 to 0.6km	0.6 to 0.8km	0.8 to 1km	1 to 1.4km	1.4 to 2km	2km and over	Total
Under 0.4km	19.3%	25.0%	22.5%	41.1%	22.9%	31.6%	76.7%	**30.8%**
0.4 to 0.6km	21.3%	26.5%	20.0%	19.5%	36.7%	51.9%	67.8%	**29.3%**
0.6 to 0.8km	15.1%	21.2%	19.8%	38.2%	46.2%	27.4%	69.0%	**28.6%**
0.8 to 1km	18.3%	29.4%	12.4%	27.4%	29.5%	52.2%	48.1%	**27.6%**
1 to 1.4km	27.1%	38.9%	21.5%	23.8%	22.0%	45.7%	60.5%	**31.3%**
1.4 to 2km	16.9%	46.6%	36.8%	39.7%	25.2%	33.8%	49.6%	**33.8%**
2km and over	30.9%	51.7%	55.2%	63.0%	56.4%	64.6%	54.8%	**53.5%**
Total	**20.7%**	**32.6%**	**23.9%**	**35.0%**	**31.6%**	**42.4%**	**59.3%**	**32.6%**

Intermodal home-work mode choice share

Home to closest PT station distance	Workplace to closes PT station distance: Under 0.4km	0.4 to 0.6km	0.6 to 0.8km	0.8 to 1km	1 to 1.4km	1.4 to 2km	2km and over	Total
Under 0.4km	0.0%	0.0%	0.0%	4.4%	0.0%	0.0%	0.0%	**0.6%**
0.4 to 0.6km	0.0%	2.3%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.5%**
0.6 to 0.8km	0.0%	2.7%	0.0%	0.0%	0.0%	1.6%	0.0%	**0.6%**
0.8 to 1km	2.1%	0.0%	0.0%	2.7%	0.0%	0.0%	0.0%	**0.9%**
1 to 1.4km	3.1%	3.4%	2.3%	1.0%	4.2%	0.0%	0.0%	**2.5%**
1.4 to 2km	11.2%	0.0%	4.3%	2.9%	1.9%	3.8%	1.5%	**4.0%**
2km and over	6.6%	2.1%	5.6%	1.7%	3.4%	0.0%	0.0%	**2.5%**
Total	**2.7%**	**1.6%**	**1.3%**	**1.8%**	**1.9%**	**1.1%**	**0.2%**	**1.7%**

Table 6.7 – Main home-work trip mode shares depending on home and workplace PT rail accessibility for the study population

Home to closest PT station distance

Length threshold	Cumulative share	Observations
1,400m	51.9%	18
3,100m	90.7%	33
10,700m	95.4%	38
13,900m	**100%**	**41**

Workplace to closes PT station distance

Length threshold	Cumulative share	Observations
540m	50.7%	18
1,250m	90.9%	36
1,450m	95.7%	38
1,500m	**97.2%**	**39**
1,900m	98.8%	40
2,600m	**100%**	**41**

Table 6.8 – Distribution of PT rail accessibility indicators for intermodal trips in the study population

mation on the household location and workplace location is only available at a 100m square grid in the Paris region for privacy issues. To get around this lack of data, euclidean direct flying distances have been nonetheless computed between PT stations as defined in MODUS and the centroid of the household and workplace square, with a maximum 71 meters error on the exact location of one end. The closest PT station node have systematically been the one considered. For the case of complex PT stations with several nodes, the closest one to the home or workplace has been considered.

Table 6.7 shows the different main home-work trip mode choices depending on these two PT rail accessibility indicators. While PT is more chosen for trips with low home-station and workplace-station distances, car is preferred for the opposite cases with high home-station and workplace-station distances, clearly defining market segments for both modes. A specific third intermodal market segment can be identified with medium to high home-station distances and low to medium workplace-station distances. This was somehow expected because the intermodality studied here is a car-based intermodality mostly relying on a car-based PT access from home. But the results are clear and it seems that these home-station and workplace-station distances enable to define threshold distance values greatly enabling or disabling intermodality practices.

When looking at the distributions of these distances for the intermodal study population in Table 6.8, it seems that the workplace-station distribution is framed with few values over 1,500m and more than 98% under this value. So this 1,500m threshold is considered as a threshold for intermodality practice, above which individuals are not intermodal. About the home-station distance, it is more spread out and it is not possible to define a similar threshold. Crossing these with the second section's observation that there are almost no intermodal trips with a home-workplace trip under 2km, a distance frame can be built to study the intermodal mode choice. First, only trips above 2km are considered. Then within these, only trips with a workplace-station distance under 1,500m are considered. Last, a distinction is made for the PT mode with the home-station distance: as 96% of the walk trip legs are under 1km, it is assumed that every PT trip with a home-station distance under 1km is a heavy PT trip while the other PT trips with a home-station distance over 1km involves another light PT mode, requiring different model parameters.

The resulting distance frame and its effect on the mode choice is presented in Table 6.9. This frame better displays intermodal uses with a 4.0% intermodal share, much higher than for the other segments under a 1% share. The car and PT shares are different in both cases, which seems to validate the use of the home-station distance threshold distinguishing rail PT from light PT first mode from home. The motorcycle, the multimodal, the walk and other modes are not studied and do not have high enough shares to be incorporated in the model. In order to avoid their effect on the model parameters and on the variable increase, they are excluded from the modelling frame.

	Home-Work trip mode share									
	PT	Car	Intermodal	Multimodal	2-3 wheelers	Walk	Other	**Total trip share**	Observations	Estimated trip number
Home-Work trip length < 2km	17.9%	25.8%	0.9%	6.6%	6.0%	42.5%	0.4%	**15.2%**	334	113,172
Home-Work trip length > 2km										
Workplace to closest station distance < 1.5km										
Home to closest station < 1km	**64.6%**	**26.5%**	**0.9%**	**2.2%**	**3.5%**	**1.8%**	**0.4%**	**32.3%**	699	239,936
Home to closest station > 1km	**54.5%**	**34.1%**	**4.0%**	**2.3%**	**4.4%**	**0.4%**	**0.2%**	**25.1%**	564	186,433
NA	0.0%	68.6%	31.4%	0.0%	0.0%	0.0%	0.0%	0.1%	3	777
Workplace to closest station distance > 1.5km	36.6%	53.8%	0.1%	4.2%	4.4%	0.9%	0.0%	13.2%	317	97,710
NA	65.2%	34.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	2	635
NA	41.0%	40.4%	2.4%	3.2%	4.4%	7.6%	1.0%	**14.0%**	298	104,015
Total	**47.9%**	**33.9%**	**1.8%**	**3.3%**	**4.3%**	**8.3%**	**0.4%**	**100%**	2,217	742,679
Observations	984	835	47	71	83	191	6	2,217		
Estimated trip number	355,803	251,696	13,497	24,448	32,203	61,998	3,034	742,679		

Table 6.9 – Mode shares for the home-work trip by distances for the study population

The last mode shares differentiated by the distances and on the PT, car and intermodal mode choice is displayed in Table 6.10. This sets up the frame for the intermodality modelling. Considering the number of available observations for each case[3], the first one with home-station distances under 1km is based on 643 observations but with few intermodal trips so its results are less strong, while the second case is more robust as it is based on 527 observations but with a 4.3% intermodal share. They represent together a 400,000 population which justifies an intermodality demand modelling attempt.

The analysis of indicators of PT accessibility has enabled to highlight specific and distinctive characteristics of the intermodality demand. This step has put forward that PT accessibility is key for better understanding the intermodality mode choice process and factors.

[3]These figures are slightly different that for the modelling exercise. This comes from the exclusion of individuals for which the travel time computation of the home-work trip was not possible because of unavailable intermediate PT travel time estimations. These few observations are used in the model with fictive 0 travel time and cost, to account for the impact of socio-economic characteristics.

	Home-Work trip mode share PT	Car	Intermodal	Total trip share	Observations	Estimated trip number
Home-Work trip length > 2km						
Workplace to closest station distance < 1.5km						
Home to closest station < 1km	**70.2%**	**28.8%**	**1.0%**	**56.1%**	643	220,938
Home to closest station > 1km	**58.9%**	**36.8%**	**4.3%**	**43.9%**	527	172,650
Total	**65.2%**	**32.3%**	**2.4%**	**100%**	1,170	393,588
Observations	718	415	37	1,170		
Estimated trip number	256,729	127,222	9,637	393,588		

Table 6.10 – Main modelled mode shares for the home-work trip for the study population

6.3.2 Representation of supply characteristics

Now that some socio-economics, demographics and PT accessibility features of the intermodality demand are identified, the intermodality supply must be characterized. This characterization is made through studying the effect of travel times and costs for the home-work trip. While these are well studied for the car mode, and a bit less for the PT mode, they are a lot less accessible for the intermodal combination of car and PT, and this subsection details how they are computed and the results of this simulation.

Travel times and costs are important descriptors of choice alternative. Indeed, the monetary cost usually is an important choice factor while the travel time is probably the most important trip characteristic in the transport research field. But both of these are not available for the alternatives not selected, and even not at all concerning the monetary cost. So they must be artificially rebuilt to better understand the individual choice process and how each impacts the final mode choice decision.

The computation of travel times is based on the modelling frame described in Chapter 5. The car network is made of "main roads" and "highways", and has dedicated connectors to 1,289 zones. The PT network is made of a transit line layer with connectors, but with an additional transit mission layer because PT vehicles are not always available on the PT lines and have specific frequencies. The PT network encompasses all of the PT modes such as the bus, the metro, the tram, the regional trains. The congestions and frequency levels considered are the peak hour ones. The software used is TransCAD with the MODUS transport model parameters and networks. Like most transport models, it does not directly enable intermodal travel time calculations, so a three steps specific process has been designed. This process is based on the fact that the studied intermodal trips are based on a car trip leg from home to a PT station, and then a final walk trip leg to access the workplace.

- The first step is designed to compute the travel times to connect each home location to each PT station. This connection is made through a time minimization over the loaded static Paris region road network. The result of this step is a travel time matrix between every home of the study population and every station in the Paris region.
- The second step uses the PT model to compute the travel times from each PT station to each workplace location considering a final walk trip leg. This connection is made through a time minimization accounting for fixed waiting times. The result of this step is a travel time matrix between every PT station and every workplace location in the Paris region.
- The third and final step computes the final intermodal travel time. In order to build these travel times, for each fixed home and workplace location, the home-work trip travel time going through every station in the Paris region is calculated. Then a travel time minimization is made to select the intermodal transfer place station. But this simple minimization is flawed and first gave wrong results. Indeed, this process first rebuilt car travel times or PT travel times by respectively yielding the closest PT station to the workplace or the closest PT station to home. In order to avoid these situations, a constraint[4] has been applied to the minimization process, in order to keep a home-station access travel time inferior to the main station-workplace travel time involving the main transport mode.

The process is illustrated in Figure 6.11.

This computation process has the advantage that it can automatically account for parking difficulties or walk time at the transfer place when these are included in the car travel time computation. But MODUS does not display enough station points to represent all of the access and exit points of stations, and all of the roads accessing every station, so the level of detail still remains a little aggregated for fine spatial analysis, especially for low travel time values. The realism of this process highly derived from the realism of travel time model for cars and PT.

The results of the computed intermodal, PT and car travel times are presented in Figure 6.12 and Figure 6.13, with an orange line representing the identity functions where both travel times are equal. Under this line, the intermodal travel times are

[4]This constraint is one possibility to avoid this intermodal travel time computation issue. Another one could have been to introduce an intermediate intermodal transfer place station choice model or to consider that only the closest station to home is chosen, as suggested by Lichere & Foulon (1999).

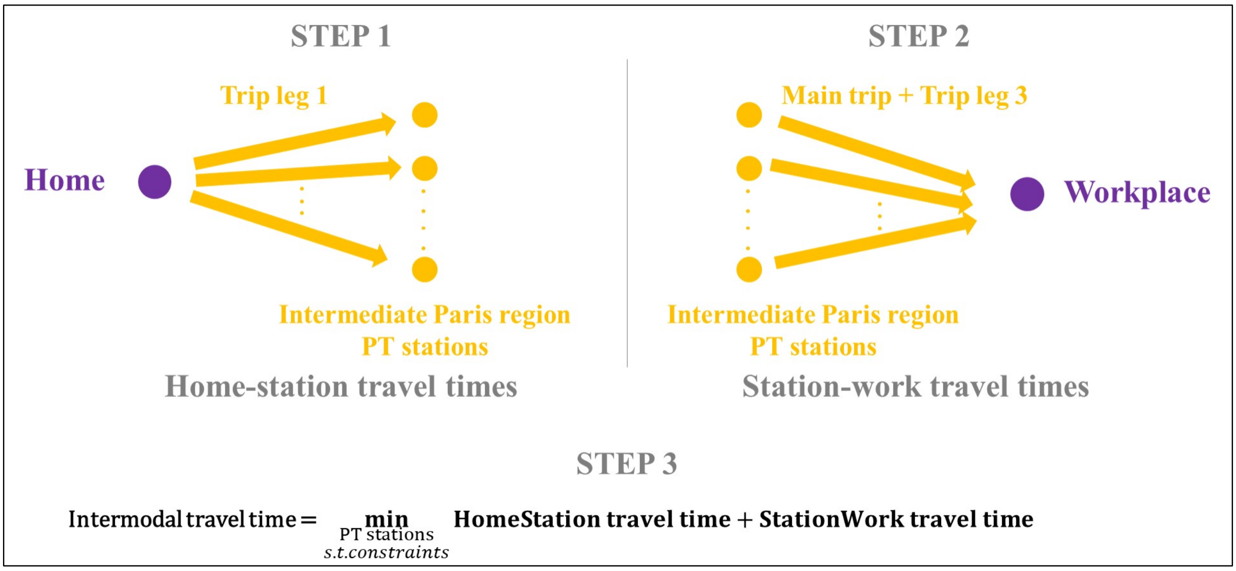


Figure 6.11 – Computation process for intermodal travel times

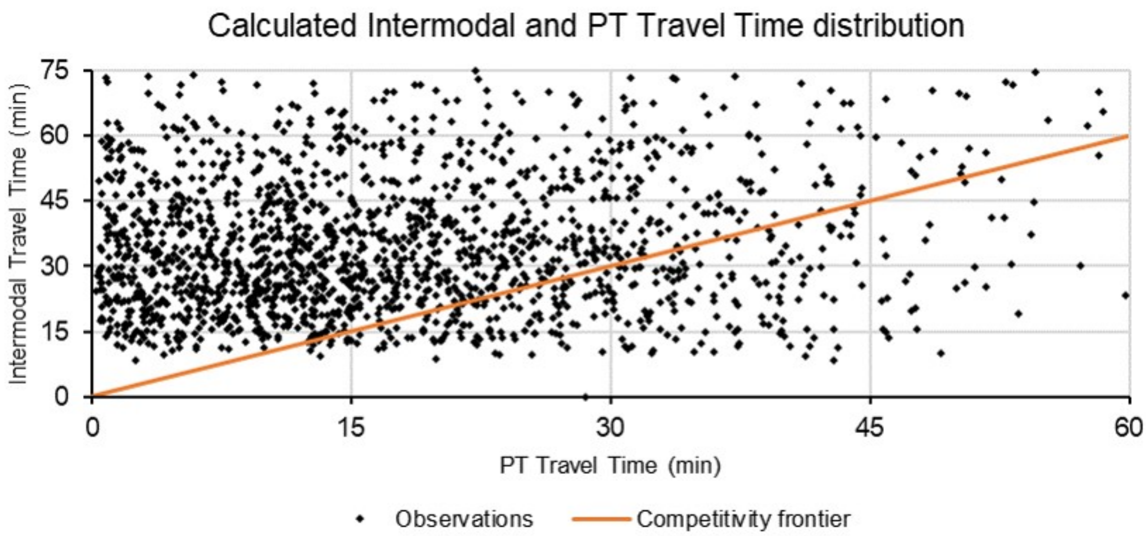


Figure 6.12 – Distribution of intermodal and PT travel times

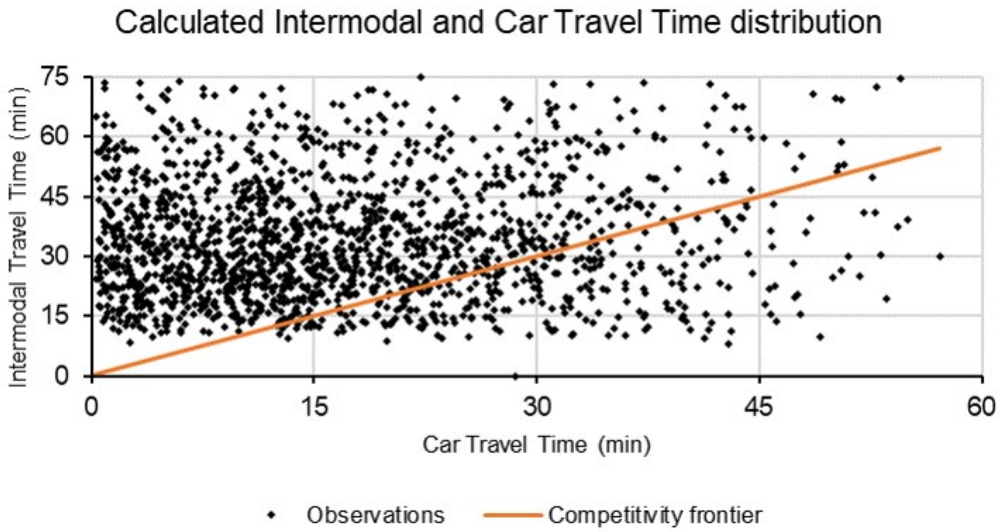


Figure 6.13 – Distribution of intermodal and car travel times

more competitive than the reference travel time. As expected, PT and intermodal modes are similar and the car travel time is more competitive, while the intermodal mode is more competitive over long distances identified by longer travel times. Overall, it seems that the intermodal travel time is often more competitive than the PT travel time, which makes sense because it is a car-accessed PT. While the car mode remains more competitive than the intermodal mode most of the time, the cost is expected to be a complementary differentiating agent for these.

Less information was available for the trip monetary cost, and so average values were decided to build this variable. The costs were calculated for each modelled mode:

- For the Car: the cost accounts for an average 7L/100km fuel consumption at a fuel price around 1.5 EUR/L with a EUR 700 insurance and an average EUR 20,000 vehicle price with a 7% yearly depreciation rate. With 40 trips of length l per month this makes a single trip cost
  $20,000 \times 7\%/(12 \times 40) + 700/(12 \times 40) + l(km) \times (7/100) \times 1.5$
  $= (4.38 + 0.105 \times l(km))$ EUR.
- For the PT: the cost is set at EUR 4 if the individual does not subscribe to the PT, or at EUR 1,250 over a year reimbursed at 50% by the company, and at 40 trips per month. This makes a single trip cost EUR 4 or
  $50\% \times 1250/(12 \times 40)$
  $= 1.30$ EUR.

– For Intermodality: The cost is calculated with the car cost to the closest station, and then with the PT cost.This makes a single trip cost $(5.68 + 0.105 \times l_{Home-Station}(km))$ EUR with a PT subscription, $(8.38 + 0.105 \times l_{Home-Station}(km))$ EUR otherwise.

This variable is averaged and is mostly used to get values of time magnitude orders in the modelling section, its construction could be improved. Figure 6.14 shows the resulting travel times and costs equilibrium for the study population of commuters who selected an intermodal mode. The figure highlights a key positioning of the intermodal alternative compared to the PT and Car alternatives: while the car alternative is the most expensive, the PT is the less expensive and the most time-consuming alternative. Intermodality is an intermediate alternative often displaying lower costs than the car and similar travel times, while providing lower travel times and higher costs than the pure PT alternative. But one must bear in mind that these results stand for the individuals of the study population who selected intermodality, and that this analysis is based on 38 observations for which all of the travel time data was available.

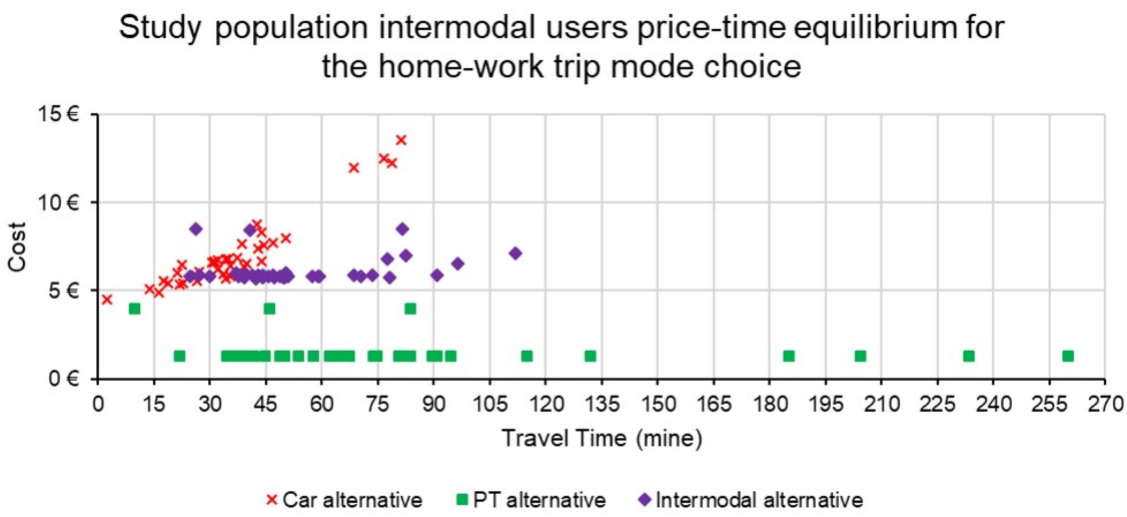


Figure 6.14 – Equilibrium of mode cost and travel times for the intermodal commuters of the study population

A next step would have been to compare the simulated results with travel time and cost observations. But these were not available, or were stated values which are perceived rather than physical values and do not enable a proper reference comparison. Specific work on the computation of intermodal travel times could then be made to evaluate the efficiency and reliability of this process, but have not been conducted in the frame of this dissertation. The model presented in the next subsection does not answer all of the modelling issues, but it is a first step toward a enabling the integration of the intermodality phenomenon within metropolitan mobility demand models.

6.3.3 Mode choice modelling for home-work trips

Now that the modelling framework is set and that all of the variables have been generated, it is possible to build an econometric model reproducing the home-work trip mode choice. The choice alternatives are presented in Figure 6.15. The goal is to estimate a statistical model to distinguish the significance level of the different variables and how they contribute to the choice. This approach gives a better understanding of the intermodality determinants and enables to confirm or to overturn hypotheses drawn in the first sections. This last subsection involves the use of the R software, and especially the *mlogit* and *stargazer* packages for running the choice model and for presenting purposes respectively. The choice frame is restricted to the active adults living in one individual households in the Paris region and making at least one home-work trip surveyed in the EGT 2010. More specifically, this study population is subdivided by filtering out the individuals with home-work trips under 2kms and with work-station distances over 1.5km, who are not likely to practice intermodality. The final modelling population is subdivided again in two modelling populations: the P1 modelling population with home-station distances under 1km with a PT mode not requiring a light PT access, and the P2 modelling population with home-station distances over 1km, with a PT mode requiring a light PT access. The choice alternatives are the public transport, the intermodal transport and the car transport. So for the P1 modelling population, PT is mostly considered as heavy PT only while for P2, the Public transport requires a first trip leg with light PT. This motivates the distinction into 2 populations without considering a model for the overall modelling population. For both, Intermodal trips are defined as PT trips with a car trip leg access or egress.

Considering the number of alternatives, that intermodality can be an independent mode, and the lack of intermodality demand models, the discrete choice model selected for the analysis is the multinomial logit(MNL). It is a simple choice model well known which is a good candidate for first intermodality demand modelling, before testing more complex models and correlation structures. The models are built on the generated time and cost alternative-specific variables to enable cost and time sensitivity estimation, with additional individual variables describing the individual socio-economic and geographic background of the choice. The reference

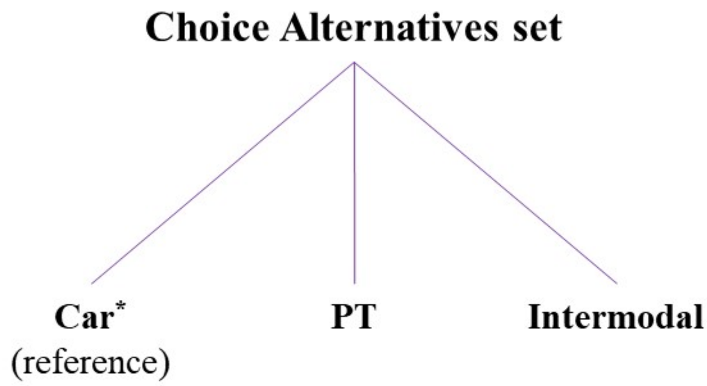


Figure 6.15 – Structure of the intermodal MNL model choice

alternative chosen is the car: it enables to study the difference between PT and intermodality, and it is an alternative with a high share less likely to be subject to unexpected variations. The final utility functions are as follows where m refers to the mode alternative, i refers to the individual of a modelling population, C is the cost variable, TT is the travel time variable and SE refers to the socio-economics individual variables and j an indicator of the socio-economics variable. As the car is the reference mode, $\beta_{car,j}$ is null. The final utility formula is:

$$V_m^i = ASC_m + \beta_{C,m} * C_m^i + \beta_{TT} * TT^i + \sum_j \beta_{m,j} * SE_j^i \tag{6.3.1}$$

The tested socio-economic variables are the same as in chapter 5 plus category variables when possible. They include descriptors of workplace characteristics – type, unicity, location commune type, parking availability, distance from home –, geographical characteristics – household location commune type –, socio-economic status – housing type, housing surface, income group, education level, socio-professional category, mobility tools holding – and individual characteristics – gender, age, disability –. The mobility tools holding variable is a dummy variable assessing whether car and PT pass subscription are held or not, to indicate the accessibility to intermodal uses rather than separate dummies for car holding and PT pass subscription. First, all of the variables were included in the model estimated by maximum likelihood estimation with the *mlogit* package within the R software. Then only significant modal and non-modal variables for P1 or P2 were kept to make the results more accessible. After this selection of socio-economic variables, cost and travel time variables were tested, with a coefficient for each alternative and only one general coefficient in turn. The final resulting models were the ones with the highest R^2 for both P1 and P2.

The model results for the population P1 and P2 are presented in Table 6.11 and display regular variables for the cost and travel time variables. The intermodal parameters of model P1 are generally not significant because there is not enough intermodal observations. The negative signs of the parameters associated to these variables is consistent, except for the intermodal cost parameter in Model P1, but this is not alarming because it is also not statistically significant. Overall, the sex variable is a little significant for model P2, but always has a positive value reflecting a slightly higher PT and intermodal use by women as opposed to the car use. Working in the agglomeration centre is a significant variable with high parameter values and significance. While it is clear that the car mode choice is discouraged by working in the down-town, it seems that it encourages intermodal practices even more than it encourages PT practice. The negative signs for the car and PT pass holding indicator parameters is counter intuitive. But it can mean that owning a car is a high incentive toward the car choice, even with a PT pass. Hopefully, the intermodal parameter has a lower magnitude than the PT parameter, illustrating that it still favours an intermediary solution between car and PT choice. The last indicator on the belonging of an individual to a higher socio-professional category – i.e. intermediate profession, craftsman, tradesman, executive and intellectual professions – clearly shows a higher effect on intermodal use. Both models are significant and have high R^2 values above 0.6. When looking at the PT parameters values, they vary a lot between model P1 and P2, suggesting that it is indeed meaningful to differentiate between light-PT access and direct heavy PT access.

This modelling step tried to tackle the issue of intermodal demand modelling. Even though trying to reduce the population in order to focus on a more intermodal subpopulation to get significant results, it is still difficult to draw general conclusions from such a restricted study case on a phenomenon which remains marginal in 2010. But the models seem to confirm the importance of socio-economic variables such as gender, workplace location, mobility tools portfolio holding and socio-professional category.

	Model P1	Model P2
parameter (standard error)		
$ASC_{intermodal}$	−107.594 (2,851.989)	10.059*** (3.709)
ASC_{PT}	5.736*** (1.613) (1.545)	6.502*** (1.340)
TT	−0.057*** (0.011)	−0.028*** (0.006)
$Cost_{car}$	−0.626*** (0.202)	−0.225 (0.141)
$Cost_{intermodal}$	9.896 (16.492)	−2.178*** (0.517)
$Cost_{PT}$	−2.696*** (0.333)	−2.708*** (0.321)
$Sex(Woman)_{intermodal}$	0.145 (0.810)	1.021* (0.583)
$Sex(Woman)_{PT}$	0.131 (0.337)	0.508 (0.384)
Workplace in the Agglomeration $Center_{intermodal}$	1.173 (0.856)	1.940*** (0.587)
Workplace ine the Agglomeration $Center_{PT}$	.984*** (0.379)	1.680*** (0.410)
Car and PT pass $holding_{intermodal}$	45.870 (2,848.937)	−0.737 (1.095)
Car and PT pass $holding_{PT}$	−3.640*** (0.882)	−3.740*** (0.847)
Higher socio-professional $category_{intermodal}$	0.152 (0.854)	1.468** (0.670)
Higher socio-professional $category_{PT}$	0.517 (0.362)	0.642 (0.420)
Observations	647	528
R^2	0.660	0.660
Log Likelihood	−147.457	−155.013
LR Test	572.465*** (df = 14)	600.776*** (df = 14)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.11 – MNL home-work trip mode choice models results

Conclusion

This chapter contributes to the state of the knowledge on intermodality in several ways. First, it gave key elements to define the intermodality concept and the importance to detail what definition is used before running any intermodality analysis. This definition must precise the trip structure, the encompassed modes and their level of detail, and the intermodal transfer places. The short literature review has enhanced one main issue for intermodality studies: they are scarce, not often published in English and much more research on this topic is expected on this subject before being able to draw general conclusions.

Second, a statistical analysis has been conducted on the population of the Paris region based on a 2010 passenger travel survey. The results are consistent with the other observations in the literature that intermodal users are more generally middle-aged between 35 and 54, women with a high education level. They more often belong to an executive, intellectual or intermediate profession socio-professional category, they are active and their workplace is most of the time located in the Paris agglomeration while their living place is located out of the city centre, in individual housing units. They also have an average to high income as opposed to the general population, and hold both a car and a PT pass subscription. Switching from an individual to a trip perspective, intermodal trips are more complex trips because they involve several trip legs. Their distance is most of the time above 2km and their trip purpose is mostly based on home-work or home-study trips. Considering these elements, most of them are radial trips connecting rural and agglomeration communes to the city centre and close agglomeration communes in the morning, with symmetrical trips back home in the afternoon. Intermodality is also made around a main public transit mode choice, with different access and egress secondary modes.

Third, intermodality modelling is challenging because it changes how trips are built and computed. A main issue arises to calculate intermodal travel times involving several modes and intermodal transfer places where delays can happen. This issue involves changing from a classical four step model frame where the assignment follows a mode choice, to joint models accounting for both simultaneously. The final challenge being to deal with the present low intermodal mode share which is expected to grow. The modelling step has highlighted strong links between PT accessibility and intermodal use. This has enabled to segment the population in order to get a sub-population with a higher intermodal trip share, by considering long home-work trips with a destination close to a PT station and an origin far from a PT station. It has also characterized intermodality as a stand-alone mode and not just a PT access mode, because it addresses another market segment than car and PT, with intermediate trip characteristics. The socio-economic variables that ended up being the most significant are the workplace location in the agglomeration centre and belonging to a higher socio-professional category. In the end, jointly holding a PT pass and a car was not as significant on intermodal use compared with car use.

Further improvements could be made by increasing the number of intermodal observations, especially with the modelled population, to get more statistically significant results. A stronger focus on the intermodal travel time computation could contribute to the intermodality research, especially by paying more attention to the choice of intermodal transfer place. Similarly, intermodal travel costs could be improved with accounting for more individual cost characteristics and parking constraints of origin, destination and intermodal transfer places. Studies could also expand to other activities and irregular intermodal trip patterns.

This chapter has mostly focused on determining key intermodality explanatory variables and market segments. The limits to intermodality demand modelling are still strong and could be lifted by incorporating specific intermodality related questions in travel surveys. While the observed intermodality is mostly a car and PT combination, the rise of new mobility services seems to suggest that a new intermodality pattern skipping the car use for mobility services may grow. This new intermodality is not well captured by the EGT 2010 data, but more actual data sets could probably enable studying more in-depth this intermodality phenomenon evolution, which would introduce a new market segment for workplaces far from a PT station.

Conclusion

This dissertation aimed on fulfilling four main objectives to support the inclusion of mobility tools holding and intermodality representation within metropolitan mobility demand models: Understand these two phenomena, estimate their respective choice process, highlight the interaction between them and put this approach in practice with the Paris region study case. In order to reach these objectives, the dissertation has provided a general description of the mobility system and the mobility modelling approach from the travel demand modelling field of research. It has then focused on the mobility tools holding phenomenon with the 2010 Paris region case study before dealing with the intermodality phenomenon. A specific study sub-population has been identified to simplify the choice structure addressed by removing the equilibrium between household and individual decision: the individuals in one individual households.

The first chapter has emphasized the need for proper field understanding to conduct mobility analyses, and has provided an analytical framework based on the supply, demand and uses characterization. It has also described mobility element measurement concepts and current data collection tools used to feed these metropolitan analyses and how sensors and national travel surveys are adapting to better account for evolving mobility uses. The need for crossing all of these data sources to enable wider analysis while taking into account the limits of each measurement method has also been put forward. This chapter has also characterized the case study of Paris, showing how this field is a proper ground for studying evolving mobility uses linked with emerging mobility services thanks to the local growth of several mobility innovations.

After the description and characterization of metropolitan mobility, the second chapter has insisted on the mobility demand modelling methodological background of this dissertation. It has presented the conept of the four step model and how its mobility decision choice structure is limited for disaggregated analysis. It has provided a general analytical frame to assess mobility demand models and has used it to compare Paris region models. This has enabled to understand the state of development of Paris region models along 22 criteria sorted out into spatio-temporal framework, demand, supply and uses blocks. The results have highlighted the need to account for more mobility phenomena including mobility tools holding and intermodality to get more detailed mobility estimations.

In order to provide answers to this need for improving these models, the third chapter has addressed the mobility tools holding phenomenon. This socio-economic phenomenon subject to behaviour evolution has been defined and conceptualized to highlight the main complexities lying behind its representing, especially regarding the time frame on which the mobility tools holding choice is made depending on durability and cost of the mobility tool, and the choice structure of the decision maker, highly dependent on interpersonal relations within households. A literature review of mobility tools holding modelling has shown that even though car ownership has been modelled for several decades and is relatively advanced, other mobility tools have often been neglected. Approaches considering a joint choice of mobility tools in portfolios have emerged in the early XXIst century and have begun to spread more in the last three years.

The fourth chapter has built on the conceptualization of the previous chapter to statistically analyse seven mobility tools from the Paris region 2010 household travel survey. These are the driving license, the car, the car parking space, the motorcycle, the bike, the PT pass subscription and the bike sharing subscription. Several analyses are proposed to understand the socio-economic explanatory variables for each mobility tools, to evaluate the co-holding of two mobility tools and last the holding combinations of different mobility tools also known as mobility tools portfolio holding. In order to avoid adding the complexity of interpersonal holding structures, a focus has been made on a study population of one-individual households. This analysis has highlighted the importance of a set of geographical and socio-economic variables. It has also provided a hierarchy of the mobility tools opposing private vehicles holding to shared services holding, with a more detailed division of the private vehicle mobility tools into the ones requiring a minimum physical condition such as bikes and motorcycles, and the others. The driving license is a specific mobility tool which can almost be considered like another socio-economic variables.

After this detailed description of the mobility tools holding phenomenon in the Paris region for the study population, modelling specifications have been proposed in the fifth chapter. Isolated modelling of mobility tools and joint modelling approaches have been set up, and the latter have shown their potential in providing insights on multiple holdings features. The introduction of trips characteristics of constrained activities and the associated modelling improvements have shown that the mobility tools holding choice is influenced by constrained trips. Adding another segment layer separating the active sub-population from the retired sub-population seems to be relevant because these display different mobility tools holding patterns, with larger average portfolios for active individuals than for retired individuals.

Last, the sixth chapter has opened the mobility tools holding modelling perspective by considering a next step in the trip-making process: intermodality modelling. Intermodality has also been defined and analysed in the Paris region, but it appears that the literature is less abundant for the intermodality demand, and that the intermodality definition is more diverse than for mobility tools holding. As a result, it is important to well specify the intermodality definition: here any trip combining different modes on trip legs, the bus and train combinations not being considered intermodal because PT subscriptions give access to both without additional fees in the Paris region. About 2% of the trips are intermodal trips and are mostly made of a car and PT combination. While their number is low and is challenging for statistical modelling, some results have shown that they provide an answer to a specific demand not well satisfied by the car or the PT only modes: the individuals living far from a PT station with a workplace close to a PT station. This observation put into question the traditional consideration of car and PT intermodality as just a PT mode with a car access.

Overall, these chapters have tackled the analysis of the magnitude and the demand fulfilled by these mobility phenomena. But the conclusions on how should the model structure evolve are less clear. Concerning the mobility tools holding phenomenon, the research is becoming more consistent and there are enough studies to validate the hierarchical observation that private vehicles are opposed to mobility services within the mobility tools holding choice process. It also seems relevant to incorporate mobility tools portfolio models into metropolitan mobility demand models because they display accessible combination effects with regards to the number of mobility tools considered. About the intermodality phenomenon, it currently is a lot less studied and not yet much represented in the trip population to build robust enough models. More studies would probably be required before implementing intermodal trips modelling into operational mobility demand models.

Main Results and Contributions

While providing answers to the objectives and the stated problems, this dissertation has enabled to reach distinctive contributions which are relevant for the development of the mobility demand modelling field. These include:

- The development of an **analytical framework for model comparison** in chapter 2 provides a proposition to ease the description and comparison of urban mobility models. It has insisted on the mobility aspects accounted for by these models rather than on specific formulations and parameter values. It is based on the specification of the spatio-temporal frame, the supply, the demand and the uses representation characterized by about 22 criteria. This table has been built to answer the lack of comparison of mobility demand models in the academic literature and to foster healthy competition between models to account for more and more detailed mobility phenomena.

- The set up of the **concept of mobility tools** is also a main contribution of this dissertation. Even though the term has been introduced by Scott & Axhausen (2006), a proper definition and conceptualization rather than an implicit one was still needed. This dissertation has proposed such a definition based on the choice-making frame related with the choice of mobility tools holding. It has especially described the importance of the choice time frame, the choice object, its demand, the choice constraints and the decision maker, and how complex it is to account for all of these elements while representing the mobility tools holding choice.

- A **hierarchy of mobility tools** has also statistically and functionally emerged from the analyses in chapter 4. This hierarchy shows an opposition between private vehicle holding and subscription to mobility services holding for the study population and for the general population. This means that most individuals are not likely to hold both categories but rather a mix of private vehicles or a mix of mobility services. This trend seems important for future forecasts and for the structure of mobility tools holding models. A less strong division appears within the private vehicle category, between tools requiring more physical condition such as the motorcycles and the bike, and the car and the car parking space.

- Chapter 5 has shown that **it is relevant to jointly model mobility tools holding to incorporate equipments substitution and complementary analysis in mobility demand models**. Indeed, the implementation of the models has shown the different impacts of several explanatory variables on the mobility tools equilibrium. The importance of constrained trips also seems important for modelling this phenomenon.

- A **definition of intermodality and a characterization of intermodal trips and users** have been proposed in chapter 6. The difficulty of providing a proper intermodality definition highlights the need to well define it before conducting a phenomenon analysis as there are several possible and relevant conceptual descriptions depending on what mode combinations are considered. Based on the exclusion of combinations of different PT modes in intermodality, most of the intermodal trips are long constrained trips made with a car and PT combination, and the intermodal users have high education levels and rather are women.

- An **exploratory modelling of intermodality demand** has also been proposed in chapter 6, which has not been observed in the literature consulted by the author. While intermodality has been modelled in route choice assignment models, it has often been considered like a sub PT mode with a car access rather than a proper independent mode. However, statistical observations show that intermodality answers a specific mobility demand different than the usual PT demand. This modelling mostly relies on a detailed segmentation based on the home and work distance to a PT station, in order to get a statistically more significant share of intermodal trip choices.

Limits and Outreach

While these contributions bring information on mobility tools holding and intermodality, a share of the stated contributions has a limited generalisation potential. The more detailed analyses are tied to the field selection and the study sub-population, namely the Paris region and the population of individuals in one individual households. As such, a generalization is not immediate and other studies on different fields and populations should be conducted to test these. But when available, the literature on the same or similar topics is mostly consistent with the observations, lifting a part of the uncertainty.

The complexity of the choice models employed in this dissertation could also be challenged. Indeed, the current choice models development generally enable more complex structures than the ones proposed in this research. As stated in Chapter 2, the approach of this research is to study mobility phenomena and evaluate their potential implementation in travel demand models rather than developing a more complex modelling structure that would suit it and be the most efficient. Considering this point, developing more complex models would not have yielded much more information than the one implemented. More practically, complex models have been tested on the mobility tools holding choice such as cross-nested logit formulations enabling cross-correlation among errors. These have not been displayed because they have shown some convergence issues, which is a downside of these models, maybe more dedicated to research than operational mobility models. Indeed, most of the model complexity comes from the structure of the error components. But this structure of the error components may not match the structure of the choice decision causing these convergence issues.

Overall, this research supports the development of metropolitan mobility models toward a more complete representing of mobility phenomena, in order to account and answer for a rising and more complex mobility demand. Addressing more accurately mobility in these models enables better understanding future evolution and trends such as shared mobility, intermodal uses through the development of Mobility as a Service (MaaS), and vehicle ownership evolution. As such, this dissertation could be complemented with other research increasing the mobility representing scope. Researching and writing this thesis has been the opportunity to highlight several questionings. Logical continuations of this work include but are not limited to:

- Investigating the relationship between mobility tools and their use more in-depths, which is a research topic that naturally rises from this study. Even though partially tackled with including characteristics of constrained trips, it could be more developed. Such research could focus on the relationship between mobility tools portfolio, mode choice and the associated trip activities. It would give results showing potential structure improvements within activity models or loop models. In order to avoid getting too many combinations, a recommendation would be to limit the number of modes, mobility tools and trip or loop main activities at first.

- Evaluating the direct impact of mobility tools holding modelling on operational metropolitan mobility models which would be an immediate follow-up. Building on the understanding of the phenomenon developed in this dissertation, it would be interesting to directly implement several candidate mobility tools holding models within existing metropolitan mobility models. Comparing their results would yield constructive feedback on the effect of this model improvement on its overall mobility results. It could be also used on several mobility models to observe with which mobility representing this improvement yields the best results.

- Assessing the structure of choice process of mobility tools holding within households which would also enable switching from a sub-population analysis to an overall population one. This work would address the decision maker issue of the choice process, whether the choice is made by an individual or in a collective frame. A more detailed survey and focus groups would be required to begin drawing a structure pattern that probably evolves with the household composition and characteristics. These would likely be linked with the durability and cost features of mobility tools, changing its rank from an individual to a collective choice with higher mobility tool durability or cost and lower individual and household purchasing power.

- Deepening the intermodality analysis with a more recent and dedicated survey would improve the general understanding of this phenomenon. Indeed, the intermodality study within this dissertation has been limited by the low number of intermodal users and trip observations in the sample. It is also likely that the phenomenon has evolved since 2010 and that it is more represented now, because intermediate modes and services are emerging and diffusing in metropolitan areas. This more focused survey could also give more information on the perception and choice of intermodal transfer places.

– Using more recent data and running diachronic analyses of the phenomena is a last update step which would give an understanding of the overall dynamics. They would enable to confirm or infirm the stability of the phenomenon evolution over time, and maybe to assess some structural behavioural evolution trends. Considering new and dynamic data also raises the question of a new continuous data collection envisioned for the EGT, with a partial yearly observation update. This procedure would probably deteriorate the quality of the data set at a fixed time period, but have a high potential for studying low-share modes or mobility tools evolution, and to better observe the diffusion of breakthrough mobility innovations.

Résumé en français

Contexte

Avec plus de 50% de la population mondiale et un taux de croissance annuel de 2%, les zones urbaines se développent rapidement dans le monde entier selon UN Habitat (2016). La mobilité est un élément clé du système métropolitain qui permet de soutenir ou de limiter localement le développement économique, social et environnemental. Alors qu'un système de mobilité métropolitaine efficace facilite la circulation des biens et des personnes en favorisant les échanges culturels et les possibilités commerciales, le secteur des transports est responsable de 25% des émissions mondiales de CO_2 en 2017 selon l'IEA (2019), et les prévisions du ITF (2019) estiment que ces émissions augmenteront de 60% entre 2015 et 2050. La compréhension de la mobilité et de son évolution est essentielle pour gérer les défis du développement durable.

Pour aller plus loin, une zone métropolitaine est un système géographique complexe où plusieurs zones de densités, de caractéristiques d'utilisation du sol et de contraintes différentes sont rassemblées au sein d'une même entité spatiale. La mobilité métropolitaine est une réponse à la complexité de l'offre et de la demande locales d'activités, reliant les différents éléments de ce système afin de faciliter les échanges et d'apporter une valeur ajoutée par des effets de réseaux. Dupuy et al. (2008) fournit des éléments illustrant que la relation entre le développement métropolitain et le développement de l'offre de mobilité sont moteurs pour la croissance urbaine. Le développement de la mobilité métropolitaine est actuellement porté par des évolutions sociétales et technologiques telles que l'émergence du télétravail, la prise en compte du développement durable, la diffusion des smartphones, des systèmes d'information et de l'automatisation. Cet environnement évolutif a contribué à accroître la connectivité de chaque individu et à répondre à la nécessité d'une connexion plus forte à un plus grand nombre de personnes et de biens. Ces évolutions ont entraîné des changements dans la manière dont les équipements de mobilité sont détenus : d'un équilibre traditionnel entre les Transports en Commun (TC) et l'automobile, plusieurs services de mobilité ont été développés au début du XXI^{eme} siècle, dans le monde entier. Ces services offrent des possibilités d'abonnement aux outils de mobilité remplaçant la possession traditionnelle. L'enthousiasme initial pour les véhicules motorisés privés est en perte de vitesse face à un intérêt renouvelé pour les modes actifs et collectifs. Une autre évolution comportementale concerne la façon dont les individus se déplacent sur un réseau. Alors qu'il était auparavant nécessaire de planifier des déplacements monomodaux à partir de points d'origine et de destination fixes, l'interconnexion accrue des services de mobilité permet des comportements plus variés combinant plusieurs modes au sein de déplacements intermodaux. Toutes ces évolutions contribuent à l'augmentation du nombre d'alternatives pour la détention d'équipement de mobilité et le choix du mode de déplacement, suggérant une interrogation sur la relation entre la détention et l'usage d'équipements de mobilité, et sur la relation entre mobilité individuelle et collective.

L'évolution sociale et technologique de la mobilité a également un impact sur la représentation de la mobilité dans les modèles de transport. En effet, alors que la planification de la mobilité était consacrée à la prévision des flux liés aux infrastructures ferroviaires ou viaires, elle doit désormais tenir compte des impacts environnementaux, en particulier des émissions de gaz à effet de serre, de la réduction des inégalités sociales associées à l'usage de l'automobile, des transports en commun et des véhicules privés et services de mobilité. Ces changements sont favorisés par une diversité modale accrue et la nécessité de promouvoir les modes actifs remet en question les théories de planification de base développées historiquement pour la gestion des investissements dans les infrastructures automobiles et ferroviaires, qui doivent évoluer pour tenir compte de ce nouvel état du système de mobilité.
D'un point de vue plus technique et méthodologique, ces changements modifient la manière dont les choix de mobilité des individus sont faits et leur inscription temporelle. Ils remettent en question l'approche agrégée historique sur laquelle se basent les modèles à quatre étapes, et soulignent la nécessité d'élargir ou de transformer les modèles afin de mieux tenir compte de l'éventail de phénomènes qui influent sur les choix de mobilité. Par exemple, alors qu'il était facile de différencier la possession d'un véhicule sur une échelle temporelle stratégique à long terme de l'utilisation d'un véhicule dans le cadre du choix du mode de transport sur une échelle temporelle tactique à court terme, les possibilités d'abonnement ajoutent une autre échelle temporelle intermédiaire rendant l'ancien cadre de décision temporel discret inadapté.

Problématique

De manière à prendre en compte la croissance des services de mobilité en lien avec une évolution de la détention d'équipements de mobilité, l'augmentation de la diversité des modes de transport disponibles et les potentiels déplacements impliquant une combinaison de modes, cette dissertation aborde la question de la représentation de la diversité modale dans les modèles de planification de la mobilité, en se concentrant sur la détention d'équipements de mobilité et la réalisation de déplacement intermodaux. Ceci implique l'analyse détaillée et des spécifications de ces deux phénomènes sur le cas d'étude de l'Ile-de-France, en interrogeant la définition, les descripteurs et les approches de modélisation adaptées pour les deux phénomènes d'étude.

La prise en compte de la détention d'équipements de mobilité introduite par Scott & Axhausen (2006); Le Vine (2011) constitue une rupture avec l'approche traditionnelle de modélisation des transports considérant l'accessibilité d'un individu ou d'un ménage à l'automobile et aux TC comme une donnée d'entrée des modèles, au lieu de la représenter comme un phénomène de mobilité à part entière. Ces premiers modèles étaient cohérents en considérant que le choix de déplacement est plus immédiat, sur une temporalité courte, alors que la possession d'un véhicule est un choix sur une temporalité plus longue. Mais cette hypothèse est moins robuste avec l'augmentation de la diversité modale et la possibilité de s'abonner et de résilier son abonnement à des services de mobilité rapidement. Conceptuellement, considérer que la détention d'équipements de mobilité est une données d'entrée des modèles de mobilité est aussi imprécis, car cela revient à considérer qu'un individu ou un ménage effectue son choix d'achat de véhicule ou de souscription à un service de mobilité indépendamment des déplacements qu'elle ou il souhaite réaliser. Inclure ce phénomène dans le processus de représentation de la mobilité est un évolution logique de la modélisation mise en avant dans Trouve & Leurent (2018).

La détention d'équipements de mobilité est également un phénomène complexe car il implique différents équipements de mobilité détenus sur différentes temporalité, avec différentes durabilités selon Cernicchiaro (2013), donnant accès à différents réseaux de transport, et qui ne sont pas toujours détenus à l'échelle individuelle mais également à l'échelle du ménage comme suggéré dans Astroza et al. (2018). Un questionnement du concept de détention d'équipements de mobilité est indispensable avant de l'évaluer. Complémentairement à ce questionnement du concept, identifier les caractéristiques expliquant le phénomène est aussi important. De manière plus explicite, ceci implique de déterminer les principales caractéristiques individuelles, socio-économiques et géographiques quantifiées au moyen d'indicateurs spécifiques, permettant le mieux d'expliquer la détention d'équipements de mobilité. Interroger les effets de combinaison des équipements de mobilité pour le même individu ou ménage est également pertinent et pourrait révéler des schéma combinatoires récurrents.

La diversité des modes de transports et des équipements de mobilité à le potentiel de soutenir une pratique plus répandue des déplacements intermodaux combinant au moins deux différents modes de transports au sein du même déplacement. Ce phénomène remet aussi en question les modèles traditionnels considérant un ensemble de choix possibles parmi un nombre fixe d'alternatives pour le choix modal, sans potentiel d'interaction entre ces alternatives. Se concentrer sur le phénomène d'intermodalité conduit naturellement à questionner ce qu'est un mode, pour quelles combinaisons modales un déplacement est considéré comme intermodal, quels sont les déterminants des individus et des usages intermodaux. Ceci permet aussi de mettre en lumière les interactions entre caractéristiques individuelles, détention d'équipements de mobilité et usages de mobilité.

Ces phénomènes appartenant au domaine de la recherche en mobilité appliquée peuvent être abordés par une analyse socio-économique systémique dans un cadre géographique spécifié, permettant de développer une approche impliquant les effets de plusieurs facteurs. Cette approche systémique implique la mobilisation de plusieurs domaines de recherche, constituant ainsi une problématique de recherche profondément pluridisciplinaire. La recherche interdisciplinaire implique l'utilisation de nombreuses méthodes variées, et une sélection doit donc être faite parmi celles permettant le mieux de répondre à la problématique. Un partie de la réponse à la complexité de la représentation de comportements individuels à l'échelle métropolitaine passe donc par l'investigation des méthodes apportant des informations sur les phénomènes d'étude, pour sélectionner des outils adaptés à ceux-ci.

En résumé, les objectifs de cette étude sont d'interroger, de décrire et d'estimer les phénomènes de détention d'équipements de mobilité et d'intermodalité pour un cas d'étude métropolitain concret, avec des méthodes issues du champ de recherche interdisciplinaire et appliqué de l'analyse de la mobilité.

Objectifs

La problématique décrite précédemment est déclinées en une série d'objectifs :

– *Améliorer la compréhension des phénomènes de détention d'équipements de mobilité et d'intermodalité* en effectuant une revue de littérature et en mettant en oeuvre des analyse statistiques pour identifier les schémas récurrents à partir de variables descriptives socio-économiques et géographiques. Ceci implique d'identifier les méthodes les plus pertinentes pour montrer des résultats éclairant les processus de choix ainsi que la mise en évidence des différents descripteurs pour chaque équipement de mobilité, et pour les combinaisons d'équipements de mobilité au sein d'un portefeuille d'équipements de mobilité incluant à la fois les précédents descripteurs d'équipements de mobilité séparés et les effets combinatoires. Pour l'intermodalité plus spécifiquement, cet objectif inclue l'analyse des caractéristiques des déplacements intermodaux.

– *Estimer la détention d'équipements de mobilité d'une part, et les usages intermodaux d'autres part, comme choix individuels* en modélisant statistiquement des taux de détention et les parts modales des déplacement intermodaux. Le principe de cette estimation n'est pas de fournir des prévisions, mais d'observer et d'interpréter les valeurs des paramètres des modèles, et leur signification en fonction des variables descriptives associées. Cette estimation permet de tester de potentielles structures de choix et segmentation de la population d'études, et de de confirmer les premiers résultats des analyses statistiques descriptives, à travers un exercice de statistiques appliquées.

– *Mettre en évidence l'interaction entre détention d'équipements de mobilité et la réalisation des déplacements* en intégrant des caractéristiques des déplacements réguliers dans l'analyse statistique de la détention d'équipements de mobilité, et en considérant la détention d'équipements de mobilité dans l'analyse de la structure du choix de mode de déplacement incluant l'intermodalité. Cet objectif se concentre sur la causalité réciproque des comportements stratégiques de choix de détention d'équipements de mobilité et tactiques de choix modal, avec une application aux déplacements pendulaires domicile-travail. L'intérêt porté à ces déplacements est justifié par les fortes contraintes de déplacements associées, qui est probablement associée à et influencée par le choix de détention de portefeuilles d'équipements de mobilité.

– *Appliquer les méthodes de modélisation à un terrain : l'Ile-de-France* pour travailler avec des réelles observations issues du jeu de données de l'enquête ménage déplacement EGT 2010. De plus, l'aire métropolitaine parisienne à connu des améliorations significatives de son système de mobilité, avec l'émergence du système de vélos partagés Vélib' en 2010, et de nombreuses incitations locales à la pratique du vélo, des transports collectifs et des déplacements intermodaux. Cette stratégie d'évolution par rapport au modèle traditionnel basé sur l'équilibre entre automobile et transports en commun en favorisant la diversité modale fait de la région parisienne un terrain d'étude pertinent pour l'étude de la détention d'équipements de mobilité, et génère de nombreuses alternatives intermodales. Cet objectif inclue de manière plus générale la compréhension du terrain pour acquérir un meilleur vue d'ensemble du phénomène et des résultats obtenus, et pour discuter de leur potentielle généralisation.

Revue du champ de recherche

Le domaine de recherche d'étude de la demande en mobilité s'est principalement développé depuis les années 1950, avec l'essor d'une approche systémique du transport en intéraction avec des caractéristiques spatiales dans Voorhees (1959), la théorisation des choix discrets par McFadden (1974); Ben-Akiva & Lerman (1985)permettant de représenter le processus de choix modal, et les nombreuses propositions d'algorithmes d'optimisation du choix d'itinéraires exposées dans Leurent (2006). Ces éléments sont rassemblés au sein du champ de la modélisation de la mobilité décrit par Bonnel (2004); Wegener (2004); Ortùzar & Willumsen (2011), et reposant sur l'intéraction entre développement urbain, génération de déplacements, distribution de déplacements, choix modal, affectation d'itinéraire, et maintenant souvent complétés d'un processus additionnel d'émission de polluants. Comme les principaux développements du domaine de la demande en mobilité ont eu lieu durant la seconde moitié du XX^{me} siècle, les études associées sont généralement basées sur un équilibre entre TC et automobile.

Parmi les nombreuses publications de ce champ de recherche, celles traitant de la détention d'équipements de mobilité et de l'intermodalité sont récentes et sont très peu confrontées, probablement parce que ces deux phénomènes ne sont pas encore assez traités dans la littérature.

Tout d'abord, les études de la détention d'équipements de mobilité ont commencées avec des premiers articles considérant la motorisation automobile comme un bien de consommation dans Cramer (1959); Trognon (1978). Des approches de modélisation combinant la consommation de plusieurs biens ont été proposées par Lancaster (1966); Rault (1969); Ashford & Sowden (1970), mais à un niveau plus théorique que pratique. Des modèles plus complexes de motorisation automobile ont été développés depuis et catégorisés dans de Jong et al. (2004a); Anowar et al. (2014a), mais sans prendre en compte les interactions entre différent équipements de mobilité. D'autres modèles considérant des équipements de mobilités de manière isolée ont également été développés dans Nagai et al. (2003); Hsu et al. (2007) pour les motocycles, et dans Muñoz et al. (2016) pour les vélos. L'abonnement à des services de mobilité possède une littérature moins fournie mais qui a des bases qualitatives avec Shaheen & Cohen (2013) par exemple. L'approche de portefeuilles d'équipements de mobilité a été introduite par Scott & Axhausen (2006) construisant un des premiers modèles traitant explicitement le phénomène de détention d'équipements de mobilité. Depuis ce papier, Le Vine (2011) a développé une analyse plus détaillée du concept de détention d'équipements de mobilité, et plusieurs publications récentes telles que Le Vine et al. (2013); Habib & Sasic (2014); Astegiano et al. (2017); Becker et al. (2017) ont enrichi ce domaine d'étude. Mais ces approches sont encore limitées par le nombre d'équipements de mobilité considérés, dépassant peu souvent la détention de quatre équipements de mobilité distincts, et aucune n'a encore été conduite en Ile-de-France.

Les recherche portant sur l'intermodalité sont nettement moins nombreuses, et pas toujours accessibles en anglais. La plupart des publications concernent l'intermodalité dans le transport de marchandises comme Jones et al. (2000); Crainic & Kim (2007). Elles soulignent la difficulté à définir l'intermodalité, montrant l'importance de préciser la définition utilisée de l'intermodalité avant de l'étudier. Il y a également souvent confusion entre les phénomènes d'intermodalité et de multimodalité étudié dans Massot (1999), qui concerne l'utilisation de différents modes pour réaliser un déplacement régulier, comme utiliser l'automobile pour aller au travail un jour, puis utiliser un système de vélo partagés un autre jour pour faire ce même déplacement. L'intermodalité concerne les déplacement impliquant l'utilisation d'une combinaison de modes, quand un individu prend un vélo pour aller à une station de bus par exemple. La littérature sur l'intermodalité a généralement un approche de statistique descriptive comme dans Lichere & Foulon (1999); Gebhardt et al. (2016); Richer et al. (2016); Oostendorp & Gebhardt (2018) par exemple. Les approches de modélisation de l'intermodalité se concentrent plus sur le choix d'itinéraire intermodal avec Florian (1977); Boile et al. (1995); Ziliaskopoulos & Wardell (2000); Leurent (2006), plutôt que sur le modélisation de la demande en intermodalité.

En considérant les développements récents des études de la détention d'équipements de mobilité et de l'intermodalité, cette dissertation est exploratoire et vise à qualifier conceptuellement et statistiquement ces phénomènes d'études avant de proposer des spécifications de modèles.

Méthodes

Diverses approches et méthodes sont nécessaires pour évaluer les phénomènes de détention d'équipements de mobilité et d'intermodalité, impliquant la recherche en urbanisme, en géographie, en sociologie, en démographie, en psychologie, en génie civil, en économie ou en développement durable. Bien que cette recherche ne peut revendiquer d'appartenir à chacun de ces domaines, des interprétations qualitatives inspirées de ceux-ci apparaissent dans ce manuscrit, avec un lien plus poussé vers les domaines de la socio-économie et du génie civil.

La première méthode employée et la plus conventionnelle est la revue de littérature. Cette méthode systématique et obligatoire développée dans chaque recherche et dans chaque doctorat permet de décrire l'état des connaissances du sujet de recherche. Elle permet de dresser le cadre de la recherche, mais aussi de définir et fixer les principaux concepts, en particulier pour des sujets dont la définition n'est pas présent ou pas consensuelle dans la littérature.

La seconde méthode méthode la plus présente est la mise en œuvre d'une description holistique du phénomène d'étude, principalement issue des analyses socio-économiques systémiques de la mobilité urbaine. Cette analyse systémique est conduite en détaillant les indicateurs d'offre et de demande, et comment leur interaction conduit à un équilibre. Plus précisément, l'approche de ce manuscrit discute la manière dont la demande est impactée par le contexte socio-économique et l'offre. Cette approche n'est pas associée directement à des outils d'analyse techniques, mais consiste en une manière générale de structure les concepts abordés tout au long de ce manuscrit.

Après ces premières méthodes générales d'aborder le sujet de recherche, des méthodes plus spécifiques et techniques sont développées: La première et principale méthode technique renvoie au domaine bien établi de la modélisation des choix discret. Elle comprend les outils mathématiques pour modéliser les comportements de choix individuel. Cette méthode est une application directe de la théorie économique de l'utilité, suggérant que chaque alternative d'un choix est conceptuellement associée à un fonction scalaire des attributs quantitatifs de l'alternative, appelée utilité. L'alternative associée à l'utilité la plus élevée est l'alternative choisie par un individu étudié. Cette approche déterministe devient probabiliste lors de l'ajout d'un terme d'erreur à la fonction d'utilité. Dans le cadre probabiliste, le poids de l'utilité de l'alternative par rapport à l'utilité des autres alternatives permet de calculer la probabilité de choisir cette alternative. La formule mathématique permettant de calculer ce poids dépend des hypothèses sur le terme d'erreur. Dans cette dissertation, des modèles de choix discret sont développés pour les choix de détention d'équipements de mobilité et de choix modal incluant une alternative intermodale, et la formulation mathématique retenue appartient à la famille logit. Cette famille logit en lien avec la distribution logistique du terme d'erreur est une des plus courantes dans la recherche en transport.

Des outils d'analyse spatiale sont le second type de méthode technique utilisés dans cette recherche, car la mobilité est le résultat de la distribution de la population et d'activité sur un terrain. Un logiciel de Système d'Information Géographique (SIG) est utilisé pour étudier la distribution des individus d'étude, de leur caractéristiques et de leur déplacements. Combiné à un package de modélisation des transports, ce logiciel est utilisé pour reproduire les temps de trajets associés aux déplacements, et pour estimer les temps de déplacements intermodaux entre des origines et des destinations données.

Un troisième type de méthode technique porte sur les statistiques descriptives pour identifier les principaux schémas des phénomènes d'étude. En plus de la production traditionnelle de moyennes et d'écarts relatifs, différentes présentation graphiques sont proposées telles que des schémas d'arbres de décision, et des diagrammes. Ces analyses sont complétées par des distances d'analyses de corrélation mettant en exergue les objets apparaissant fréquemment ensemble ou séparés. Ces méthodes sont appliquées à un jeu de données issu d'une enquête ménage déplacement de la région parisienne, sans avoir été développé spécifiquement pour cette recherche.

Pour décrire la structure des modèles de mobilité métropolitaine, une approche confrontant les différentes théories de modélisation est mise en œuvre. Elle est basée sur une synthèse de documentations techniques des modèles, sur l'identification d'indicateurs comparables et sur la définition d'une typologie permettant un accès simplifié aux pouvoir explicatif des modèles, et mettant en évidence les différences entre modèles.

Structure

Cette thèse est divisée en 6 chapitres. Les deux premiers chapitres décrivent le cadre de cette recherche, tandis que les trois chapitres suivants se concentrent sur le phénomène de la détention d'équipements de mobilité, avant un dernier chapitre consacré à l'analyse de l'intermodalité.

Le **Chapitre 1** décrit l'approche descriptive systémique de la mobilité métropolitaine. Son objectif est double : décrire les objets du système de mobilité et évaluer les potentielles sources de données nourrissant ces analyses. Il établit le cadre thématique de l'offre, de la demande et des usages utilisé pour analyser la mobilité, en lien avec les caractéristiques du terrain, ainsi que les concepts généraux abordés dans cette recherche. Il discute également la capacité d'observer des phénomènes de mobilité à partir de données issues de différentes sources avec différentes portées et différents niveau de fiabilité.

Le **Chapitre 2** porte sur les méthodes de planification des déplacements. Ce chapitre examine les techniques de modélisation utilisées pour représenter la mobilité métropolitaine et la nécessité d'étendre le champ de ces outils de planification de la mobilité. Il contribue à cette thèse en commençant par décrire la structure générale dont sont issus la plupart des modèles récents. Ensuite, il définit un cadre d'analyse des modèles mettant en évidence les caractéristiques et la spécificité de chaque modèle. Enfin, il fournit une comparaison des modèles appliqués en région parisienne, illustrant la nécessité d'une représentation plus complète de la mobilité.

Le **Chapitre 3** aborde le phénomène de détention d'équipements de mobilité. Les objectifs de ce chapitre sont la définition et la conceptualisation du phénomène de détention d'équipements de mobilité, ainsi que la caractérisation de sa diversité à travers la notion de portefeuilles d'équipements de mobilité, la proposition d'une revue de littérature sur les techniques de modélisation qui lui sont consacrées. Cette revue débute avec des modèles agrégés représentant des équipements de mobilité isolés avant de présenter des approches de portefeuilles combinant plusieurs équipements de mobilité dans le même processus de choix. Ces éléments constituent un point de départ pour des analyses statistiques plus spécifiques.

Le **Chapitre 4** interroge le phénomène de détention d'équipements de mobilité comme un choix au niveau du ménage ou de l'individu. Il évalue statistiquement la diversité des équipements de mobilité en Ile-de-France, incluant le permis de conduire, la voiture, le parking automobile, le vélo, le passe TC et l'abonnement aux services de vélos partagés. Des descripteurs socio-économiques, démographiques et géographiques de chaque équipement de mobilité isolé sont étudiés, avant de s'intéresser aux schémas récurrents de la combinaison de plusieurs équipements de mobilité au sein d'un portefeuille. Ceci implique plusieurs méthodes statistiques comme des représentations statistiques développées spécialement pour cette étude au niveau individuel. Cette analyse repose sur un traitement de l'enquête ménage déplacement EGT 2010 de l'Ile-de-France, avec un traitement particulier du sous-population d'étude simplifiant la problématique du choix individuel versus collectif : les individus seuls dans leur ménage. Cette sous-population d'étude est également étudiée dans les chapitres suivants.

Le **Chapitre 5** fournit des propositions de modélisation de combinaisons d'équipements de mobilité ainsi que des estimations pour les populations étudiées. Après avoir établi des modèles pour chaque équipement de mobilité séparément, un modèle combiné de portefeuille est construit. Cette approche est affinée en identifiant les portefeuilles les plus courants et en distinguant des segments de population associés à des besoins différents: la sous-population des actifs. Cette approche conduit à prendre en compte l'effet des caractéristiques du déplacement contraint domicile-travail sur le choix de détention d'équipements de mobilité. Ce dernier élément requiert la reconstruction des temps de trajet des déplacements non réalisés à l'aide d'un modèle de transport pour le déplacement domicile-travail, liant le choix de déplacement au choix de détention d'équipements de mobilité.

Le **Chapitre 6** réunit la détention d'équipements de mobilité et la réalisation de déplacements intermodaux pour étudier leur interaction, avec les déplacements domicile-travail. De manière intuitive, la pratique de l'intermodalité requiert des portefeuilles de mobilité spécifiques. Premièrement, le phénomène d'intermodalité est défini et étudié. Deuxièmement, une étude statistique des descripteurs des déplacements intermodaux et des individus intermodaux est réalisée, montrant des schémas socio-économiques et géographiques récurrents. Troisièmement, une approche de modélisation basée sur segments spécifiques de demande favorisant l'étude de l'intermodalité est proposée.

Principaux résultats et contributions

Tout en apportant des réponses aux objectifs et à la problématique, ce mémoire propose des contributions distinctes qui sont pertinentes pour le développement de la recherche en modélisation de la mobilité. Parmi celles-ci, il est possible de citer :

- L'élaboration d'un **cadre analytique de comparaison de modèles** dans le chapitre 2 fournit une solution pour faciliter la description et la comparaison des modèles. Ce cadre met en exergue les aspects de la mobilité pris en compte par les modèles plutôt que les formulations et les valeurs spécifiques de paramètres. Il est basé sur la spécification du cadre spatio-temporel, de l'offre, de la demande et de la représentation des usages caractérisée par 22 critères. Ce tableau a été construit pour répondre au manque de comparaison des modèles de mobilité dans la littérature académique et pour favoriser une concurrence positive entre les modèles afin de prendre en compte de plus en plus de phénomènes de mobilité, et manière plus détaillée.

- La description détaillée du **concept d'équipement de mobilité** est également un apport majeur de ce mémoire. Même si le terme a été introduit par Scott & Axhausen (2006), une définition et une conceptualisation explicites plutôt qu'implicites étaient encore nécessaires. Cette thèse propose une telle définition basée sur l'environnement du choix d'équipement de mobilité. Elle décrit notamment l'importance du cadre temporel de choix, de l'objet de choix, de sa demande, des contraintes de choix et du décideur, ainsi que de la complexité de la prise en compte de tous ces éléments dans la représentation du choix d'équipements de mobilité.

- Une **hiérarchie des équipements de mobilité** a également émergé statistiquement et fonctionnellement des analyses du chapitre 4. Cette hiérarchie montre une opposition entre la détention de véhicules privés et la détention d'abonnements à des services de mobilité. Cela signifie que la plupart des individus ne détiennent pas les deux catégories mais plutôt une combinaison de véhicules privés ou une combinaison de services de mobilité. Cette tendance semble importante pour les futures prévisions et pour la structure des modèles de mobilité. Une séparation moins forte apparaît au sein de la catégorie des véhicules particuliers, entre les équipements nécessitant plus de capacité physique comme les motos et le vélo, et la voiture et le parking automobile.

- Le chapitre 5 montre qu'**il est pertinent de modéliser conjointement les équipements de mobilité pour incorporer la substitution d'équipements et l'analyse de complémentarité dans les modèles de mobilité**. En effet, l'utilisation des modèles montre les différents impacts de plusieurs variables explicatives sur l'équilibre des équipements de mobilité. L'importance des déplacements contraints semble également importante pour modéliser ce phénomène.

- Une **définition de l'intermodalité et une caractérisation des déplacements et des utilisateurs intermodaux** sont proposées dans le chapitre 6. La difficulté à fournir une définition appropriée de l'intermodalité met en évidence la nécessité de bien la définir avant de procéder à une analyse du phénomène, car il existe plusieurs descriptions conceptuelles possibles et pertinentes selon les combinaisons de modes envisagées. En excluant les différentes combinaisons de modes TC de l'intermodalité, la plupart des voyages intermodaux sont de longs trajets contraints effectués avec une combinaison voiture et TC, et les utilisateurs intermodaux sont majoritairement éduqués et de sexe féminin.

- Une **modélisation exploratoire de la demande d'intermodalité** est également proposée dans le chapitre 6, modélisation non-observée dans la littérature consultée. Bien que l'intermodalité ait été modélisée dans des modèles d'affectation de choix d'itinéraire, elle est souvent considérée comme un mode secondaire de TC avec accès automobile, plutôt qu'un mode à part entière. Cependant, les observations statistiques montrent que l'intermodalité répond à une demande de mobilité spécifique et différente de la demande en TC habituelle. Cette modélisation repose principalement sur une segmentation détaillée basée sur la distance domicile-travail à une station de TC, afin d'obtenir une part statistiquement plus importante de choix de déplacements intermodaux.

- Un résultat connexe du chapitre 1 est une **perspective mondiales de la motorisation motocycliste et automobile** quantifiant les trajectoires de croissance dans les pays en développement et montrant un début de baisse de la motorisation automobile dans certains pays développés. Les tendances actuelles dans les pays en développement semblent être plus fortes que celles précédemment observées dans les pays développés, car elles se produisent dans un paradigme avec des technologies pleinement développées. La place de la motorisation motocycliste traditionnellement considérée comme un premier accès bon marché à la motorisation avant une motorisation automobile est remise en cause. Cette étude expose également la croissance potentielle de la motorisation liée à l'augmentation du PIB par habitant, qui peut et doit être gérée par des politiques adaptées pour éviter les problèmes de congestion et d'émissions de GES.

Limites et perspectives

Malgré les informations sur la détention d'équipements de mobilité et sur l'intermodalité que ces contributions apportent, une partie des contributions mentionnées a une ampleur limitée. Les analyses plus détaillées sont liées au choix du terrain et à la sous-population d'étude, à savoir l'Ile-de-France et la population des individus seuls dans un ménage. Une généralisation n'est donc pas immédiate et d'autres études sur différents terrains et populations doivent être menées pour les valider. Pourtant, lorsqu'elle est disponible, la littérature sur ces sujets est pour la plupart conforme aux observations, levant une partie de l'incertitude.

La complexité des modèles de choix discret utilisés dans cette thèse pourrait également être remise en question. En effet, le développement actuel des modèles de choix discrets permet généralement une structure beaucoup plus complexe que celle proposée. Comme indiqué au chapitre 2, l'approche de cette recherche consiste à étudier les phénomènes de mobilité et à évaluer leur mise en œuvre potentielle dans les modèles de mobilité plutôt que de développer une structure de modélisation plus complexe parfaitement calibrée et qui serait la plus efficace. Cependant, l'élaboration de modèles plus complexes n'aurait pas permis d'obtenir beaucoup plus d'informations que les modèles dévelopés dans ce manuscrit. Plus concrètement, des modèles complexes ont été testés sur les équipements de mobilité avec des formulations cross-nested logit permettant une corrélation croisée entre les erreurs. Ces modèles n'ont pas été présentés car des problèmes de convergence sont apparus, ce qui est un inconvénient des modèles complexes, peut-être plus appropriés à la recherche que les modèles de mobilité opérationnels. En effet, la majeure partie de la complexité des modèles provient de la structure spécifique des composantes d'erreur. Mais cette structure des erreurs peut ne pas correspondre avec la structure de décision du choix, causant ces problèmes de convergence.

Dans l'ensemble, cette recherche soutient l'évolution des modèles de mobilité métropolitaine vers une représentation plus complète des phénomènes de mobilité, afin de prendre en compte et de répondre à une demande de mobilité croissante et plus complexe. Aborder la mobilité de manière plus précise dans ces modèles permet de mieux comprendre l'évolution et les tendances futures telles que la mobilité partagée, les utilisations intermodales grâce au développement du concept de Mobility as a Service (MaaS), et l'évolution de la détention d'équipements. À ce titre, elle pourrait être complétée par d'autres recherches augmentant la portée de la représentation de la mobilité. La recherche et la rédaction de cette thèse ont été l'occasion de mettre en évidence plusieurs questionnements. Les suites logiques de ce travail incluent :

- Etudier la relation entre les équipements de mobilité et leur usage de manière plus approfondie est un sujet de recherche qui découle naturellement de cette étude. Même s'il est partiellement abordée avec l'inclusion des caractéristiques du choix du mode de déplacement contraint, elle pourrait être plus développée. Cette recherche pourrait se concentrer sur la relation entre le portefeuille d'équipements de mobilité, le choix du mode de transport et les activités de déplacement associées. Elle donnerait des résultats montrant les améliorations potentielles de la structure des modèles d'activité ou des modèles à boucle de déplacement. Afin d'éviter d'obtenir trop de combinaisons, il serait recommandé de limiter dans un premier temps le nombre de modes, d'outils de mobilité et d'activités principales de déplacement ou de boucle.

- Evaluer l'impact direct de la modélisation des équipements de mobilité sur les modèles opérationnels de mobilité métropolitaine constituerait une suite immédiate. En s'appuyant sur la compréhension du phénomène développée dans cette thèse, il serait intéressant de mettre en œuvre directement plusieurs possibles modèles d'équipements de mobilité dans un modèle de mobilité métropolitaine existants. La comparaison de leurs résultats permettrait d'obtenir des informations constructives sur l'effet de l'amélioration de ce modèle sur ses résultats généraux en matière de mobilité. Il serait également possible de répéter ces observations sur différents modèles de mobilité pour observer avec quelle représentation de la mobilité initiale cette amélioration donne les meilleurs résultats.

- Evaluer la structure ddu choix d'équipements de mobilité au sein des ménages permettrait également de passer d'une analyse de sous-population à une analyse générale de la population. Ce travail aborderait la question des preneurs de décisions dans le processus de choix, que le choix soit fait par un individu ou dans un cadre collectif. Une enquête plus détaillée et des groupes de travail seraient nécessaires pour commencer à construire un schéma de cette structure qui évolue probablement avec la composition et les caractéristiques des ménages. Celle-ci serait probablement liée à la durabilité et au coût des équipements de mobilité, modifiant le rang de choix individuel à choix collectif avec une durabilité ou un coût plus élevé et un pouvoir d'achat individuel et du ménage plus faible.

- Approfondir l'analyse de l'intermodalité par une enquête plus récente et ciblée permettrait d'améliorer la compréhension générale de ce phénomène. En effet, l'étude de l'intermodalité dans le cadre de cette thèse est limitée par le faible nombre de pratiquants et d'observations de voyages intermodaux dans l'échantillon. Il est aussi probable que le phénomène ait évolué depuis 2010 et qu'il soit davantage représenté aujourd'hui, car les modes et services intermédiaires semblent se répandre dans les zones métropolitaines. Cette enquête plus ciblée pourrait également donner plus d'informations sur la perception et le choix des lieux de transfert intermodal.

– Uiliser des données plus récentes et exécuter des analyses diachroniques des deux phénomènes étudiés est une étape de mise à jour qui permettrait de comprendre leurs caracteristiques dynamiques . Ceci permettrait de confirmer ou d'infirmer la stabilité de l'évolution du phénomène dans le temps, et peut-être d'évaluer certaines tendances structurelles de l'évolution du comportement. La prise en compte de nouvelles données et dynamiques soulève également la question d'un nouveau format de collecte de données en continu envisagé pour l'EGT, avec une mise à jour annuelle partielle des observations. Cette procédure détériorerait probablement la qualité de l'ensemble des données à une année données, mais elle présente un fort potentiel pour étudier les modes à faible part modale ou l'évolution des équipements de mobilité, et pour mieux observer la diffusion des innovations en matière de mobilité.

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Appendix A

Mobility in a Metropolitan Area data

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Porto Alegre	m		5.68	5.56	5.61	5.74	6.04	6.24	6.38	6.55	6.55		6.89	6.85	6.85	6.84	6.53			
	sigma		1.23	1.22	1.19	1.17	1.17	1.15	1.12	1.13	1.10		1.11	1.09	1.11	1.08	1.07			
Rio de Janeiro	m		5.63	5.50	5.52	5.68	5.95	6.14	6.26	6.50	6.48		6.69	6.72	6.70	6.66	6.36			
	sigma		1.23	1.22	1.22	1.20	1.20	1.22	1.22	1.19	1.20		1.21	1.16	1.16	1.19	1.21			
Salvador de Bahia	m		5.25	5.16	5.05	5.24	5.56	5.76	5.99	6.15	6.18		6.50	6.41	6.43	6.41	6.08			
	sigma		1.32	1.35	1.32	1.27	1.28	1.29	1.29	1.30	1.27		1.25	1.26	1.28	1.24	1.20			
Sao Paulo	m		5.81	5.71	5.67	5.76	6.08	6.29	6.48	6.63	6.61		6.97	6.91	6.91	6.89	6.58			
	sigma		1.23	1.23	1.20	1.18	1.21	1.16	1.16	1.12	1.11		1.11	1.12	1.15	1.16	1.10			
Shanghai	m					5.84	5.96	6.08	6.32	6.52	6.61	6.74	6.92	7.03	7.14	7.21	7.23			
	sigma					0.77	0.78	0.81	0.75	0.75	0.73	0.72	0.71	0.72	0.73	0.70	0.67			
Hanoi	m											-1.91		-1.61		-1.36		-1.26		
	sigma											1.30		1.27		1.27		1.27		
Madrid	m									7.66	7.61	7.54	7.46	7.44	7.65	7.45	7.29	7.23		
	sigma									1.03	1.10	1.06	1.08	1.11	1.08	1.11	1.15	1.18		
Manila	m	5.85			5.71			6.00			6.18			6.37			6.37			
	sigma	0.83			0.75			0.74			0.76			0.75			0.72			
Dubai	m	6.46								7.09						7.43				
	sigma									1.84										
Delhi	m					6.23	6.31	6.38	6.59	6.67	6.86	7.05	7.08	7.16	7.15	7.21	7.26	7.35		
	sigma												0.64							
Hyderabad	m		4.18	4.21	4.32	4.43	4.46	4.55	4.75	4.57	4.68	4.79	4.67	4.68	4.61	4.65	4.67			
	sigma		1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34	1.34			
Casablanca	m					6.22			6.35		6.44	6.43								
	sigma	0.75							0.76											
Cape Town	m				6.00								6.85	6.82	6.61					
	sigma		1.19						1.17			1.12						1.14		
Bogota	m											5.22	5.28	5.30	5.37	5.39	5.32			
	sigma									1.03	1.02	1.02	1.01	0.95	0.97	0.96	0.95			
Auckland	m	8.09					8.11					8.12				8.23			8.33	
	sigma		0.75			0.78					0.77									
Montreal	m					7.75						7.91							8.07	
	sigma					0.82						0.80								

Table A.1 – Parameters of the income lognormal distribution for the worldwide metropolitan analysis

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Sum of squared errors	Threshold
Porto Alegre	observed(car)		223	232	240	248	258	266	277	292	308		345	366								
	model(car)		234	224	228	239	264	280	293	309	309		340	336								
	Delta2(car)		113.7	59.3	149.2	88.1	33.9	209.3	242.8	287.2	1.1		19.7	873.3							2077.6	1000.8
	observed(motorcycle)		27	30	34	39	43	49	55	62	66		75	78								
	model(motorcycle)		33	30	31	35	43	50	55	63	63		78	76								
	Delta2(motorcycle)		40.1	0.0	10.0	15.4	0.0	1.5	0.0	0.6	13.0		14.8	4.6							100.1	1000.8
Rio de Janeiro	observed(car)		156	164	169	173	178	184	192	201	213		236	251								
	model(car)		165	158	159	168	183	194	201	216	215		228	230								
	Delta2(car)		79.8	30.2	94.3	29.2	18.1	108.3	92.2	227.5	5.3		62.8	441.9							1189.5	1001.3
	observed(motorcycle)		9	11	12	14	16	19	22	26	29		36	39								
	model(motorcycle)		12	10	10	13	17	21	23	29	29		35	36								
	Delta2(motorcycle)		9.7	0.1	3.6	2.9	0.2	4.2	1.1	9.7	0.1		0.8	10.7							43.1	1012.3
Salvador de Bahia	observed(car)		104	109	112	117	122	129	137	145	155		175	186								
	model(car)		112	108	104	112	125	135	146	154	156		173	168								
	Delta2(car)		61.5	0.3	77.2	25.0	9.1	29.5	81.9	91.4	2.1		4.8	341.3							724.0	1002.1
	observed(motorcycle)		7	9	11	12	14	16	19	24	28		37	41								
	model(motorcycle)		11	10	8	11	15	18	23	27	28		37	34								
	Delta2(motorcycle)		9.9	0.2	5.4	3.1	0.6	3.9	13.3	9.1	0.1		0.3	41.6							87.4	1024.3
Sao Paulo	observed(car)		266	276	284	292	302	315	333	352	371		405	424								
	model(car)		282	272	269	277	309	331	350	366	364		403	397								
	Delta2(car)		268.0	12.6	232.1	226.8	47.6	244.1	317.4	194.4	44.9		3.0	754.6							2345.5	1000.5
	observed(motorcycle)		22	24	27	30	34	40	48	56	60		71	74								
	model(motorcycle)		28	25	24	26	35	43	50	56	55		74	70								
	Delta2(motorcycle)		34.7	0.4	10.3	15.8	1.1	6.2	5.2	0.3	24.2		9.6	11.7							119.5	1004.4
Shanghai	observed(car)					17	22	26	30	34	39	45	51	59	68	76	86					
	model(car)					18	21	23	31	38	41	47	56	63	69	74	75					
	Delta2(car)					0.3	1.4	6.5	0.8	15.8	7.6	4.9	28.0	10.0	2.7	1.8	122.2				201.9	1012.0
	observed(motorcycle)													17	17	17	17					
	model(motorcycle)													17	17	17	17					
	Delta2(motorcycle)													0.0	0.2	0.0	0.1				0.3	1000.1
Hanoi	observed(car)										47						74					
	model(car)										49						73					
	Delta2(car)										2.5						1.1				3.5	1026.4
	observed(motorcycle)										426		543				680					
	model(motorcycle)										448		538				670					
	Delta2(motorcycle)										474.1		22.6				115.8				612.5	1014.6
Madrid	observed(car)									538	513	511	512	506	501	505	519	533				
	model(car)									512	513	514	516	516	512	516	519	520				
	Delta2(car)									681.6	0.0	14.7	15.7	93.8	130.5	130.3	0.1	188.8			1255.5	1000.0
	observed(motorcycle)									41	42	43	44	45	46	48	50	52				
	model(motorcycle)									42	43	45	46	47	42	46	50	51				
	Delta2(motorcycle)									0.8	1.3	1.9	2.9	1.4	13.4	1.9	0.0	1.2			24.8	1000.6
Manila	observed(car)													37	37	37	37	36				
	model(car)													37	37	37	37	37				
	Delta2(car)													0.0	0.1	0.0	0.3	0.2			0.7	1000.5
	observed(motorcycle)													61	62	68	67	73				
	model(motorcycle)													66	63	66	66	72				
	Delta2(motorcycle)													20.1	0.8	3.8	3.2	2.2			30.0	993.9

Table A.2 – Calibration results for the consumption distribution for the worldwide metropolitan analysis (1/2)

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Sum of squared errors	Threshold
Dubai	observed(car)								484	518	493	470	462	473	499	504						
	model(car)								486	486	486	486	485	485	485	485						
	Delta2(car)								3.8	996.6	57.6	247.0	553.0	149.8	202.1						2209.9	995.2
	observed(motorcycle)								9	10	10	10	10	10	11							
	model(motorcycle)								9	10	10	10	10	11	11							
	Delta2(motorcycle)								0.1	0.0	0.0	0.0	0.1	0.1	0.4	0.0					0.7	993.0
Delhi	observed(car)					97	98	104	111	117	124		140	145	150	156	164					
	model(car)					94	98	102	113	118	130		144	149	148	153	156					
	Delta2(car)					8.4	0.2	3.5	5.9	1.4	28.8		17.7	19.3	4.3	11.8	51.5				152.8	1000.7
	observed(motorcycle)					193	204	215	229	239	250		277	290	303	318	335					
	model(motorcycle)					193	201	208	231	241	264		291	301	300	308	315					
	Delta2(motorcycle)					0.1	9.8	48.0	4.5	5.1	183.9		211.1	122.4	10.1	95.9	372.0				1062.7	1000.6
Hyderabad	observed(car)		17	19	20	22	25	28	32	38	42	46	51									
	model(car)		17	18	22	26	27	32	44	33	39	46	39									
	Delta2(car)		0.1	0.7	1.6	12.2	5.2	14.8	130.8	24.3	12.4	0.0	156.0								358.0	1011.6
	observed(motorcycle)		85	93	103	113	124	137	155	174	191	206	224									
	model(motorcycle)		85	90	107	126	132	151	197	154	179	207	178									
	Delta2(motorcycle)		0.3	11.7	16.2	160.4	61.1	192.6	1815.5	395.1	145.8	0.9	2118.8								4918.2	1005.5
Casablanca	observed(car)					144	148	163	169	178	188	196	205	209	212	215						
	model(car)					140	149	157	166	177	189	185	200	210	219	229						
	Delta2(car)					12.2	0.3	30.0	9.8	0.5	0.5	120.8	25.8	0.2	48.0	198.6					446.8	975.9
	observed(motorcycle)					3	3	3	3	3	4	4	4	4	4	4						
	model(motorcycle)					3	3	3	3	3	4	4	4	4	4	5						
	Delta2(motorcycle)					0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1					0.2	971.7
Cape Town	observed(car)													269	278	285	293	293	291	293		
	model(car)													277	265	284	288	292	296	300		
	Delta2(car)													77.0	168.9	1.4	23.7	2.5	19.8	39.9	333.1	1006.2
	observed(motorcycle)													15	16	15	16	15	15	14		
	model(motorcycle)													16	16	15	15	15	15	14		
	Delta2(motorcycle)													0.3	0.2	0.1	0.7	0.0	0.1	0.3	1.7	993.5
Bogota	observed(car)									83	88	96	107	115	123	131	136					
	model(car)									94	98	98	108	111	127	131	116					
	Delta2(car)									121.8	96.8	2.9	2.1	17.0	16.4	0.0	424.1				681.2	976.9
	observed(motorcycle)									18	21	26	34	42	48	53	57					
	model(motorcycle)									25	28	28	35	38	52	55	42					
	Delta2(motorcycle)									55.9	55.5	4.0	1.6	13.1	11.2	3.6	235.5				380.4	966.6
Auckland	observed(car)	398					509					550				614			694			
	model(car)	466					484					503				607			706			
	Delta2(car)	4553.8					610.5					2291.1				47.8			154.7		7657.9	1001.0
	observed(motorcycle)	10					13					20				23			27			
	model(motorcycle)	13					14					15				21			29			
	Delta2(motorcycle)	10.0					0.4					28.8				4.6			6.4		50.2	998.5
Montreal	observed(car)					278						278							261			
	model(car)					281						273							264			
	Delta2(car)					8.9						33.2							7.7		49.8	1000.1
	observed(motorcycle)					7						9							11			
	model(motorcycle)					7						9							11			
	Delta2(motorcycle)					0.0						0.0							0.0		0.0	1000.6

Table A.3 – Calibration results for the consumption distribution for the worldwide metropolitan analysis (2/2)

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Porto Alegre	Estimated m	5.53	5.63	5.73	5.83	5.93	6.03	6.12	6.22	6.32	6.42	6.52	6.62	6.72	6.81	6.91	7.01	7.11	7.21	7.31	7.41	7.50	7.60	7.70	7.80	7.90	8.00
	Observed(car)		223	232	240	248	258	266	277	292	308		345	366													
	Model(car)	222	230	238	246	254	262	271	279	288	297	306	315	324	333	342	352	361	371	380	390	400	410	420	430	440	450
	Observed(motorcycle)		27	30	34	39	43	49	55	62	66		75	78													
	Model(motorcycle)	29	32	34	37	40	43	46	50	53	57	61	65	70	75	79	85	90	96	102	108	115	121	128	136	143	151
Rio de Janeiro	Estimated m	5.50	5.59	5.68	5.77	5.86	5.95	6.03	6.12	6.21	6.30	6.39	6.48	6.57	6.66	6.75	6.84	6.93	7.02	7.11	7.20	7.28	7.37	7.46	7.55	7.64	7.73
	Observed(car)		156	164	169	173	178	184	192	201	213		236	251													
	Model(car)	158	163	168	173	178	183	188	193	198	204	209	215	220	226	232	238	244	250	256	262	269	275	281	288	295	301
	Observed(motorcycle)		9	11	12	14	16	19	22	26	29		36	39													
	Model(motorcycle)	10	11	13	14	15	17	18	20	22	24	26	29	31	34	37	40	44	47	51	55	60	64	69	74	80	86
Salvador de Bahia	Estimated m	5.07	5.17	5.27	5.37	5.47	5.58	5.68	5.78	5.88	5.98	6.09	6.19	6.29	6.39	6.49	6.60	6.70	6.80	6.90	7.01	7.11	7.21	7.31	7.41	7.52	7.62
	Observed(car)		104	109	112	117	122	129	137	145	155		175	186													
	Model(car)	105	109	113	117	122	126	131	136	141	146	151	156	162	167	173	179	185	191	197	203	209	216	223	229	236	243
	Observed(motorcycle)		7	9	11	12	14	16	19	24	28		37	41													
	Model(motorcycle)	9	10	11	12	14	15	17	19	21	23	25	28	31	34	37	41	45	49	53	58	63	69	75	81	87	94
Sao Paulo	Estimated m	5.63	5.72	5.82	5.91	6.01	6.11	6.20	6.30	6.39	6.49	6.58	6.68	6.77	6.87	6.96	7.06	7.15	7.25	7.34	7.44	7.53	7.63	7.72	7.82	7.91	8.01
	Observed(car)		266	276	284	292	302	315	333	352	371		405	424													
	Model(car)	265	274	283	293	302	312	321	331	341	351	361	371	382	392	403	413	424	435	445	456	467	478	489	499	510	521
	Observed(motorcycle)		22	24	27	30	34	40	48	56	60		71	74													
	Model(motorcycle)	23	25	28	30	33	36	39	43	46	50	54	59	63	68	73	79	85	91	97	104	111	119	127	135	144	153
Estimated m	Estimated m	5.48	5.62	5.75	5.89	6.02	6.16	6.29	6.43	6.56	6.70	6.84	6.97	7.11	7.24	7.38	7.51	7.65	7.79	7.92	8.06	8.19	8.33	8.46	8.60	8.74	
	Observed(car)					17	22	26	30	34	39	45	51	59	68	76	86										
	Model(car)	10	11	14	16	19	22	26	30	34	40	45	52	59	67	76	86	97	108	121	134	149	165	181	199	218	237
	Observed(motorcycle)													17	17	17	17										
	Model(motorcycle)	18	18	18	18	18	18	18	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	16	16	16
Hanoi	Estimated m	-2.97	-2.86	-2.75	-2.64	-2.53	-2.42	-2.31	-2.20	-2.09	-1.98	-1.87	-1.76	-1.65	-1.54	-1.43	-1.32	-1.21	-1.10	-0.99	-0.88	-0.76	-0.65	-0.54	-0.43	-0.32	-0.21
	Observed(car)	17									47						74										
	Model(car)	28	30	32	35	37	39	42	45	48	51	54	58	61	65	69	73	77	82	86	91	96	102	107	113	119	125
	Observed(motorcycle)	313									426		543				680										
	Model(motorcycle)	210	234	260	287	316	346	377	409	441	474	507	540	573	605	637	668	698	726	754	780	804	827	849	868	886	903
Madrid	Estimated m	8.02	7.97	7.93	7.88	7.84	7.80	7.75	7.71	7.66	7.62	7.57	7.53	7.48	7.44	7.39	7.35	7.30	7.26	7.21	7.17	7.12	7.08	7.03	6.99	6.94	6.90
	Observed(car)	536	547	550	500	518	520	518	547	538	513	511	512	506	501	505	519	533									
	Model(car)	506	507	508	508	509	510	511	511	512	513	514	515	515	516	517	518	518	519	520	521	522	522	523	524	525	526
	Observed(motorcycle)	30	30	30	28	30	32	36	40	41	42	43	44	45	46	48	50	52									
	Model(motorcycle)	36	37	37	38	39	40	41	41	42	43	44	45	46	47	47	48	49	50	51	52	53	54	55	56	57	58
Manila	Estimated m	5.74	5.79	5.83	5.88	5.92	5.97	6.01	6.06	6.10	6.15	6.19	6.24	6.28	6.33	6.37	6.42	6.46	6.51	6.55	6.60	6.64	6.69	6.73	6.78	6.82	6.87
	Observed(car)													37	37	37	37	36									
	Model(car)	38	38	38	38	38	38	37	37	37	37	37	37	37	37	37	37	37	36	36	36	36	36	36	36	36	36
	Observed(motorcycle)													61	62	68	67	73									
	Model(motorcycle)	34	36	38	40	42	44	46	48	50	53	55	58	60	63	66	69	72	75	78	82	85	89	92	96	100	104

Table A.4 – Estimation results for the motorization trends for the worldwide metropolitan analysis (1/2)

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Dubai	Estimated m	6.48	6.55	6.62	6.69	6.76	6.83	6.90	6.97	7.04	7.11	7.18	7.25	7.32
	Observed(car)								484	518	493	470	462	473
	Model(car)	489	488	488	488	487	487	487	487	486	486	486	485	485
	Observed(motorcycle)								9	10	10	10	10	10
	Model(motorcycle)	8	8	8	8	8	9	9	9	9	10	10	10	11
Delhi	Estimated m	5.90	6.00	6.09	6.19	6.29	6.38	6.48	6.58	6.67	6.77	6.87	6.97	7.06
	Observed(car)		70	86	91	97	98	104	111	117	124		140	145
	Model(car)	79	83	88	92	97	102	107	113	118	124	130	136	143
	Observed(motorcycle)		164	178	185	193	204	215	229	239	250		277	290
	Model(motorcycle)	161	170	179	189	198	209	219	230	241	253	265	277	289
Hyderabad	Estimated m	4.27	4.31	4.34	4.38	4.41	4.44	4.48	4.51	4.55	4.58	4.62	4.65	4.68
	Observed(car)		17	19	20	22	25	28	32	38	42	46	51	
	Model(car)	20	21	23	24	25	27	28	30	32	33	35	37	39
	Observed(motorcycle)		85	93	103	113	124	137	155	174	191	206	224	
	Model(motorcycle)	99	105	111	117	123	129	136	143	150	157	165	172	180
Casablanca	Estimated m	6.08	6.12	6.15	6.19	6.23	6.27	6.30	6.34	6.38	6.42	6.45	6.49	6.53
	Observed(car)					144	148	163	169	178	188	196	205	209
	Model(car)	114	121	127	135	142	149	157	165	174	182	191	200	210
	Observed(motorcycle)					3	3	3	3	3	4	4	4	4
	Model(motorcycle)	2	2	3	3	3	3	3	3	3	4	4	4	4
Cape Town	Estimated m	5.98	6.04	6.11	6.18	6.25	6.32	6.39	6.46	6.53	6.60	6.67	6.73	6.80
	Observed(car)													269
	Model(car)	232	235	239	243	246	250	254	257	261	265	269	272	276
	Observed(motorcycle)													15
	Model(motorcycle)	18	18	18	17	17	17	17	17	16	16	16	16	16
Bogota	Estimated m	5.00	5.02	5.05	5.07	5.10	5.13	5.15	5.18	5.20	5.23	5.25	5.28	5.30
	Observed(car)									83	88	96	107	115
	Model(car)	64	67	70	74	78	81	85	89	94	98	103	107	112
	Observed(motorcycle)									18	21	26	34	42
	Model(motorcycle)	10	11	13	14	16	18	20	23	25	28	31	35	39
Auckland	Estimated m	8.09	8.09	8.09	8.10	8.10	8.10	8.10	8.11	8.11	8.11	8.11	8.12	8.12
	Observed(car)	398					509					550		
	Model(car)	468	471	473	476	478	480	483	485	487	490	492	494	497
	Observed(motorcycle)	10					13					20		
	Model(motorcycle)	13	13	13	13	13	14	14	14	14	14	14	14	14
Montreal	Estimated m	7.66	7.68	7.71	7.73	7.76	7.78	7.80	7.83	7.85	7.88	7.90	7.92	7.95
	Observed(car)					278						278		
	Model(car)	286	285	284	282	281	280	278	277	276	274	273	272	270
	Observed(motorcycle)					7						9		
	Model(motorcycle)	6	6	7	7	7	7	8	8	8	8	9	9	9

		2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Dubai	Estimated m	7.39	7.46	7.52	7.59	7.66	7.73	7.80	7.87	7.94	8.01	8.08	8.15	8.22
	Observed(car)	499	504											
	Model(car)	485	484	484	484	483	483	483	483	482	482	482	481	481
	Observed(motorcycle)	11												
	Model(motorcycle)	11	11	11	12	12	12	13	13	13	14	14	15	15
Delhi	Estimated m	7.16	7.26	7.35	7.45	7.55	7.64	7.74	7.84	7.94	8.03	8.13	8.23	8.32
	Observed(car)	150	156	164										
	Model(car)	149	156	163	170	178	185	193	201	209	217	226	235	244
	Observed(motorcycle)	303	318	335										
	Model(motorcycle)	301	314	327	340	354	368	381	395	409	423	438	452	466
Hyderabad	Estimated m	4.72	4.75	4.79	4.82	4.85	4.89	4.92	4.96	4.99	5.03	5.06	5.09	5.13
	Observed(car)													
	Model(car)	41	44	46	48	51	53	56	59	62	65	68	71	75
	Observed(motorcycle)													
	Model(motorcycle)	189	197	206	215	224	233	243	252	262	272	283	293	304
Casablanca	Estimated m	6.56	6.60	6.64	6.68	6.71	6.75	6.79	6.83	6.86	6.90	6.94	6.97	7.01
	Observed(car)	212	215											
	Model(car)	219	229	239	249	260	271	282	293	304	316	328	340	352
	Observed(motorcycle)	4	4											
	Model(motorcycle)	4	5	5	5	5	5	6	6	6	7	7	7	8
Cape Town	Estimated m	6.87	6.94	7.01	7.08	7.15	7.22	7.29	7.35	7.42	7.49	7.56	7.63	7.70
	Observed(car)	278	285	293	293	291	293							
	Model(car)	280	284	288	292	296	300	304	308	312	316	320	324	328
	Observed(motorcycle)	16	15	16	15	15	14							
	Model(motorcycle)	15	15	15	15	15	14	14	14	14	14	14	13	13
Bogota	Estimated m	5.33	5.35	5.38	5.40	5.43	5.45	5.48	5.50	5.53	5.55	5.58	5.60	5.63
	Observed(car)	123	131	136										
	Model(car)	117	122	128	133	139	145	151	157	163	170	176	183	190
	Observed(motorcycle)	48	53	57										
	Model(motorcycle)	43	47	52	58	63	69	76	83	90	98	107	115	125
Auckland	Estimated m	8.12	8.12	8.12	8.13	8.13	8.13	8.13	8.14	8.14	8.14	8.14	8.15	8.15
	Observed(car)		614			694								
	Model(car)	499	502	504	506	509	511	513	516	518	520	523	525	527
	Observed(motorcycle)		23			27								
	Model(motorcycle)	14	15	15	15	15	15	15	15	15	16	16	16	16
Montreal	Estimated m	7.97	8.00	8.02	8.05	8.07	8.09	8.12	8.14	8.17	8.19	8.21	8.24	8.26
	Observed(car)					261								
	Model(car)	269	268	266	265	264	263	261	260	259	258	256	255	254
	Observed(motorcycle)					11								
	Model(motorcycle)	10	10	10	11	11	12	12	12	13	13	14	14	15

Table A.5 – Estimation results for the motorization trends for the worldwide metropolitan analysis (2/2)

Appendix B

Paris region Mobility Tools holding data

B.1 Paris region socio-economic variables data

		Adults with a driving license share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	77.6%	0%	20.4%
	In-agglomeration - Dense communes	73.0%	-7%	36.7%
	In-agglomeration - Predominantly urbanized communes	80.1%	3%	24.0%
	In-agglomeration - Other communes	83.1%	6%	7.6%
	Out-of-agglomeration - Main communes	82.6%	6%	4.4%
	Out-of-agglomeration - Other communes	88.6%	14%	3.0%
	Rural communes	92.4%	18%	3.8%
Housing type	Other	81.0%	4%	0.2%
	Collective housing	74.1%	-5%	69.0%
	Individual Housing	86.9%	11%	30.8%
Housing surface	Under 50 m²	69.6%	-11%	21.3%
	51m² to 70m²	74.2%	-5%	23.4%
	71m² to 90m²	76.4%	-2%	23.4%
	91m² to 110m²	84.9%	9%	13.6%
	111m² to 150m²	88.8%	14%	12.0%
	151m² and over	92.2%	18%	6.2%
	N/A	65.8%	-16%	0.3%
Household monthly income	Less than €1,200	51.2%	-34%	9.1%
	€1,200 to €1,600	60.8%	-22%	9.1%
	€1,600 to €2,000	71.0%	-9%	9.7%
	€2,000 to €2,400	74.4%	-5%	9.2%
	€2,400 to €3,000	78.6%	1%	11.6%
	€3,000 to €3,500	84.5%	8%	10.1%
	€3,500 to €4,500	88.7%	14%	13.2%
	€4,500 to €5,500	92.8%	19%	8.3%
	Over €5,500	91.0%	17%	12.4%
	N/A and Refusal	79.0%	1%	7.2%
Household head age	Household head < 25	66.7%	-14%	2.2%
	25 ≤ Household head ≤ 62	77.2%	-1%	76.8%
	62 < Household head	82.3%	5%	21.0%
Number of individuals per household	1	81.7%	5%	20.8%
	2	82.0%	5%	31.0%
	3	75.6%	-3%	18.4%
	4 and over	72.9%	-7%	29.7%
	Total	78.0%		100%

Table B.1 – Adults holding a driving license share by socio-economic variables (1/3)

		Adults with a driving license share	Relative deviation from the mean	Adult share
Age	18 to 24	**44.1%**	**-43%**	9.6%
	25 to 34	**75.2%**	**-4%**	18.9%
	35 to 54	**81.9%**	**5%**	40.5%
	55 to 64	**87.1%**	**12%**	15.1%
	65 to 74	**87.3%**	**12%**	8.4%
	75 an above	**79.0%**	**1%**	7.5%
Mobility disabled	Yes	**67.0%**	**-14%**	9.2%
	No	**79.3%**	**2%**	89.7%
	N/A	**68.0%**	**-13%**	1.1%
Gender	Man	**84.8%**	**9%**	46.9%
	Woman	**72.0%**	**-8%**	53.1%
Highest level of education	Never attended school	**17.3%**	**-78%**	0.8%
	Currently studying	**45.3%**	**-42%**	6.8%
	Primary school	**58.0%**	**-26%**	5.5%
	Secondary school	**58.8%**	**-25%**	7.7%
	High school	**76.2%**	**-2%**	20.7%
	High school degree	**77.9%**	**0%**	10.9%
	Apprenticeship and other higher education	**72.5%**	**-7%**	0.5%
	Higher education	**86.8%**	**11%**	13.4%
	Bachelor degree and over	**91.7%**	**17%**	33.4%
	N/A	79.4%	2%	0.3%
Occupation	Worker	**84.5%**	**8%**	58.6%
	+Full-time job	***85.8%***	***10%***	*52.5%*
	+Part-time job	***73.2%***	***-6%***	*6.1%*
	Retired	**85.9%**	**10%**	19.8%
	Homemaker	**53.0%**	**-32%**	5.9%
	Unemployed	**61.4%**	**-21%**	6.8%
	Student	**44.8%**	**-43%**	6.6%
	Inactive and N/A	**54.6%**	**-30%**	2.3%
Socio-professional category	No professional activity	**44.8%**	**-43%**	6.5%
	Farmer	67.3%	-14%	0.1%
	Employee	**69.7%**	**-11%**	17.4%
	Blue-collar worker	**73.2%**	**-6%**	9.8%
	Intermediate profession	**88.2%**	**13%**	17.2%
	Craftsman, Retailer and Business leader	**92.4%**	**18%**	2.8%
	Executive and Intellectual profession	**93.7%**	**20%**	17.7%
	Retired	**85.9%**	**10%**	19.8%
	N/A	**50.9%**	**-35%**	8.8%
Total		**78.0%**		100%

Table B.2 – Adults holding a driving license share by socio-economic variables (2/3)

		Adults with a driving license share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	66.0%	-15%	31.9%
	Unkown and N/A	83.7%	7%	68.1%
Number of daily trips made	Less than 2	74.1%	-5%	27.8%
	3	78.4%	1%	10.4%
	4	79.9%	2%	20.2%
	5	82.6%	6%	10.0%
	6	83.3%	7%	9.9%
	7 and above	85.2%	9%	14.2%
	N/A	60.5%	-22%	7.5%
	Total	78.0%		100%

Table B.3 – Adults holding a driving license share by socio-economic variables (3/3)

For workers and students		Adults with a driving license share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	77.2%	-4%	26.1%
	In-agglomeration - Dense communes	81.9%	2%	32.7%
	In-agglomeration - Predominantly urbanized communes	84.8%	5%	14.0%
	In-agglomeration - Other communes	88.2%	10%	5.8%
	Out-of-agglomeration - Main communes	91.2%	13%	2.5%
	Out-of-agglomeration - Other communes	90.7%	13%	1.1%
	Rural communes	94.5%	18%	1.5%
	N/A	72.6%	-10%	16.2%
Unicity of workplace location	Yes, out of home	82.1%	2%	79.6%
	Yes, home	82.9%	3%	3.3%
	No	79.8%	-1%	15.2%
	N/A	12.9%	-84%	1.9%
Car parking available at work/study	Yes	87.0%	8%	50.3%
	No	74.0%	-8%	29.0%
	N/A	73.7%	-8%	20.8%
Bike parking available at work/study	Yes	85.7%	6%	48.2%
	No	76.8%	-4%	31.1%
	N/A	73.8%	-8%	20.7%
	Total	80.5%		100%

Table B.4 – Worker or student adults holding a driving license share by socio-economic variables

		Average number of cars	Relative deviation from the mean	Car holding rate	Relative deviation from the mean	Multiple car holding rate	Relative deviation from the mean	Household share
IAU commune type	Agglomeration center communes	0.49	-50%	44.6%	-37%	4.3%	-82%	23.5%
	In-agglomeration - Dense communes	0.90	-9%	70.2%	-1%	17.5%	-26%	36.5%
	In-agglomeration - Predominantly urbanized communes	1.26	27%	85.5%	20%	34.6%	45%	22.7%
	In-agglomeration - Other communes	1.43	44%	89.8%	26%	45.1%	90%	7.0%
	Out-of-agglomeration - Main communes	1.31	33%	86.4%	21%	37.7%	58%	4.2%
	Out-of-agglomeration - Other communes	1.67	69%	95.3%	34%	58.8%	147%	2.7%
	Rural communes	1.80	82%	96.0%	35%	65.2%	174%	3.4%
Housing type	Other	0.63	-37%	53.7%	-25%	8.4%	-65%	0.2%
	Collective housing	0.77	-23%	63.2%	-11%	12.4%	-48%	72.4%
	Individual Housing	1.58	60%	92.6%	30%	53.9%	127%	27.4%
Housing surface	Under 50 m²	0.46	-53%	42.3%	-41%	3.8%	-84%	27.0%
	51m² to 70m²	0.86	-13%	71.1%	0%	13.4%	-44%	24.5%
	71m² to 90m²	1.07	8%	80.3%	13%	23.7%	0%	21.2%
	91m² to 110m²	1.41	43%	90.9%	28%	43.6%	83%	11.7%
	111m² to 150m²	1.61	63%	93.9%	32%	56.3%	137%	10.4%
	151m² and over	1.88	90%	98.1%	38%	70.3%	196%	4.9%
	N/A	0.85	-14%	62.8%	-12%	20.8%	-12%	0.3%
Household monthly income	Less than €1,200	0.32	-67%	30.3%	-57%	1.9%	-92%	10.4%
	€1,200 to €1,600	0.55	-44%	49.1%	-31%	5.4%	-77%	10.5%
	€1,600 to €2,000	0.71	-28%	62.9%	-12%	6.9%	-71%	11.3%
	€2,000 to €2,400	0.83	-16%	70.3%	-1%	11.8%	-51%	10.3%
	€2,400 to €3,000	1.02	3%	76.0%	7%	22.4%	-6%	11.8%
	€3,000 to €3,500	1.19	21%	83.9%	18%	31.9%	34%	9.4%
	€3,500 to €4,500	1.37	38%	88.3%	24%	41.6%	75%	11.8%
	€4,500 to €5,500	1.42	44%	90.7%	27%	44.7%	88%	7.4%
	Over €5,500	1.55	57%	92.5%	30%	50.5%	112%	10.4%
	N/A and Refusal	1.09	10%	75.0%	5%	28.7%	21%	6.8%
Household head age	Household head < 25	0.37	-63%	32.4%	-55%	4.3%	-82%	2.8%
	25 ≤ Household head ≤ 62	1.04	5%	72.7%	2%	26.2%	10%	74.5%
	62 < Household head	0.92	-7%	71.3%	0%	18.3%	-23%	22.7%
Total		0.99		71.3%		23.8%		100%

Table B.5 – Households holding a car share by socio-economic variables (1/2)

		Average number of cars	Relative deviation from the mean	Car holding rate	Relative deviation from the mean	Multiple car holding rate	Relative deviation from the mean	Household share
Number of workers per household	0	0.77	-22%	62.3%	-13%	13.8%	-42%	28.6%
	1	0.78	-21%	63.6%	-11%	12.8%	-46%	39.0%
	2+	1.43	45%	88.4%	24%	45.9%	93%	32.4%
Number of mobility disabled	0	1.02	3%	72.7%	2%	24.9%	5%	87.3%
	1+	0.81	-19%	61.5%	-14%	16.4%	-31%	12.7%
Average number of daily trips per household member	0	1.09	10%	76.3%	7%	27.6%	16%	34.3%
	above 0 to 1	1.18	19%	78.0%	9%	33.5%	41%	20.8%
	above 1 to 2	0.91	-8%	68.7%	-4%	19.2%	-19%	22.7%
	more than 2	0.75	-25%	59.8%	-16%	13.4%	-44%	22.2%
Total		0.99		71.3%		23.8%		100%

Table B.6 – Households holding a car share by socio-economic variables (2/2)

For household with workers or students		Average number of cars	Relative deviation from the mean	Car holding rate	Relative deviation from the mean	Multiple car holding rate	Relative deviation from the mean	Household share
Households with at list one working/study IAU commune type	Agglomeration center communes	**0.91**	**-13%**	**66.5%**	**-9%**	**21.1%**	**-22%**	35.5%
	In-agglomeration - Dense communes	**1.12**	**7%**	**77.4%**	**6%**	**29.3%**	**9%**	44.4%
	In-agglomeration - Predominantly urbanized communes	**1.40**	**33%**	**86.9%**	**19%**	**45.0%**	**66%**	19.3%
	In-agglomeration - Other communes	**1.52**	**45%**	**90.6%**	**24%**	**50.8%**	**88%**	8.3%
	Out-of-agglomeration - Main communes	**1.64**	**56%**	**93.5%**	**28%**	**56.9%**	**110%**	3.6%
	Out-of-agglomeration - Other communes	**1.76**	**68%**	**96.1%**	**31%**	**67.3%**	**149%**	1.6%
	Rural communes	**1.77**	**68%**	**94.9%**	**30%**	**61.6%**	**128%**	2.1%
	N/A	**1.14**	**8%**	**74.1%**	**1%**	**31.9%**	**18%**	19.8%
Households with at list one working/study type	Unique out of home	**1.08**	**3%**	**74.7%**	**2%**	**28.4%**	**5%**	87.6%
	Unique at home	**1.22**	**16%**	**78.2%**	**7%**	**34.6%**	**28%**	4.4%
	Not unique	**1.12**	**7%**	**73.9%**	**1%**	**30.4%**	**12%**	20.9%
	N/A	0.82	-22%	64.6%	-12%	17.7%	-35%	0.1%
Households with at list one working/study	Car parking	**1.21**	**15%**	**80.6%**	**10%**	**34.0%**	**26%**	62.3%
	Bike parking	**1.17**	**11%**	**78.3%**	**7%**	**32.6%**	**20%**	60.1%
Total		1.05		73.2%		27.0%		100%

Table B.7 – Households with at least one worker or student, holding a driving license share by socio-economic variables

		Parking type		Parking status					
		Private parking	Public parking	Owned	Rented	Paid	Free and Other	Car share	Household share
Housing type	Other	82.4%	17.5%	15.2%	41.8%	8.0%	35.0%	0.1%	0.2%
	Collective	71.4%	28.6%	30.0%	29.2%	7.6%	33.1%	56.0%	72.4%
	Individual	75.5%	24.5%	64.8%	4.9%	0.6%	29.7%	43.7%	27.4%
IAU commune type	Agglomeration center communes	69.3%	30.7%	28.4%	35.1%	22.7%	13.8%	11.6%	23.5%
	In-agglomeration - Dense communes	69.4%	30.6%	36.1%	23.1%	5.0%	35.8%	33.1%	36.5%
	In-agglomeration - Predominantly urbanized communes	74.7%	25.3%	49.8%	14.2%	0.5%	35.4%	28.7%	22.7%
	In-agglomeration - Other communes	75.3%	24.7%	52.7%	12.5%	0.5%	34.3%	10.1%	7.0%
	Out-of-agglomeration - Main communes	73.6%	26.4%	48.5%	15.0%	0.9%	35.6%	5.6%	4.2%
	Out-of-agglomeration - Other communes	82.4%	17.7%	68.2%	7.3%	0.1%	24.4%	4.5%	2.7%
	Rural communes	83.4%	16.6%	72.4%	5.5%	0.2%	21.9%	6.1%	3.4%
Housing surface	Under 50 m²	61.0%	39.0%	15.2%	33.5%	12.4%	38.8%	12.6%	27.0%
	51m² to 70m²	69.1%	30.9%	27.5%	27.9%	6.0%	38.6%	21.2%	24.5%
	71m² to 90m²	74.5%	25.5%	42.1%	21.0%	3.4%	33.4%	22.9%	21.2%
	91m² to 110m²	75.9%	24.1%	55.2%	13.1%	2.8%	29.0%	16.6%	11.7%
	111m² to 150m²	79.1%	20.9%	68.3%	6.4%	2.1%	23.2%	16.8%	10.4%
	151m² and over	80.5%	19.5%	74.7%	3.0%	0.9%	21.4%	9.4%	4.9%
	N/A	74.3%	25.7%	27.8%	36.7%	9.5%	26.0%	0.2%	0.3%
Household monthly income	Under€800	66.5%	33.6%	19.0%	26.9%	4.8%	49.3%	0.8%	3.5%
	€800 to€1,200	61.5%	38.5%	21.2%	26.2%	10.2%	42.4%	2.6%	6.9%
	€1,200 to€1,600	61.8%	38.2%	21.4%	25.7%	6.1%	46.8%	5.9%	10.5%
	€1,600 to€2,000	68.5%	31.5%	28.6%	27.6%	5.5%	38.4%	8.1%	11.3%
	€2,000 to€2,400	72.9%	27.0%	34.8%	25.7%	4.0%	35.4%	8.6%	10.3%
	€2,400 to€3,000	72.7%	27.3%	41.2%	20.8%	4.1%	33.9%	12.1%	11.8%
	€3,000 to€3,500	74.4%	25.6%	45.7%	19.0%	4.6%	30.6%	11.3%	9.4%
	€3,500 to€4,500	75.5%	24.5%	50.1%	15.0%	3.4%	31.5%	16.2%	11.8%
	€4,500 to€5,500	78.6%	21.4%	57.5%	15.0%	2.6%	25.0%	10.6%	7.4%
	Over€5,500	74.5%	25.5%	57.2%	12.8%	5.6%	24.4%	16.2%	10.4%
	N/A andRefusal	75.7%	24.3%	57.1%	13.0%	4.7%	25.2%	7.5%	6.8%
	Total	**73.0%**	**26.7%**	**45.1%**	**18.6%**	**4.5%**	**31.5%**	99.8%	100%

Table B.8 – Previous night car parking type and status shares by socio-economic variables

		Average number of car parking space held	Relative deviation from the mean	Car parking space holding rate	Relative deviation from the mean	Multiple car parking space holding rate	Relative deviation from the mean	Household share
IAU commune type	Agglomeration center communes	**0.31**	**-50%**	**28.8%**	**-40%**	**2.2%**	**-83%**	23.5%
	In-agglomeration - Dense communes	**0.53**	**-16%**	**43.7%**	**-9%**	**8.6%**	**-35%**	36.5%
	In-agglomeration - Predominantly urbanized communes	**0.80**	**27%**	**59.7%**	**24%**	**18.3%**	**39%**	22.7%
	In-agglomeration - Other communes	**0.93**	**48%**	**64.7%**	**35%**	**25.0%**	**90%**	7.0%
	Out-of-agglomeration - Main communes	**0.83**	**32%**	**58.6%**	**22%**	**20.6%**	**56%**	4.2%
	Out-of-agglomeration - Other communes	**1.25**	**97%**	**76.3%**	**59%**	**40.8%**	**210%**	2.7%
	Rural communes	**1.40**	**122%**	**78.6%**	**64%**	**48.1%**	**265%**	3.4%
Housing type	Other	0.39	-38%	31.0%	-36%	7.9%	-40%	0.2%
	Collective housing	**0.45**	**-28%**	**39.8%**	**-17%**	**5.3%**	**-60%**	72.4%
	Individual Housing	**1.11**	**75%**	**70.2%**	**46%**	**34.1%**	**159%**	27.4%
Housing surface	Under 50 m²	**0.23**	**-64%**	**21.4%**	**-55%**	**1.1%**	**-92%**	27.0%
	51m² to 70m²	**0.48**	**-25%**	**42.6%**	**-11%**	**4.5%**	**-66%**	24.5%
	71m² to 90m²	**0.68**	**7%**	**55.0%**	**15%**	**11.1%**	**-16%**	21.2%
	91m² to 110m²	**0.96**	**52%**	**69.2%**	**44%**	**24.1%**	**83%**	11.7%
	111m² to 150m²	**1.20**	**90%**	**75.8%**	**58%**	**38.3%**	**191%**	10.4%
	151m² and over	**1.46**	**131%**	**82.8%**	**72%**	**52.1%**	**295%**	4.9%
	N/A	0.55	-13%	35.3%	-26%	18.3%	39%	0.3%
Household monthly income	Less than €1,200	**0.15**	**-76%**	**14.6%**	**-70%**	**0.5%**	**-96%**	10.4%
	€1,200 to €1,600	**0.26**	**-59%**	**24.1%**	**-50%**	**1.7%**	**-87%**	10.5%
	€1,600 to €2,000	**0.40**	**-37%**	**35.7%**	**-26%**	**3.3%**	**-75%**	11.3%
	€2,000 to €2,400	**0.50**	**-20%**	**43.9%**	**-9%**	**5.9%**	**-55%**	10.3%
	€2,400 to €3,000	**0.63**	**0%**	**50.4%**	**5%**	**11.0%**	**-17%**	11.8%
	€3,000 to €3,500	**0.77**	**22%**	**58.7%**	**22%**	**16.4%**	**24%**	9.4%
	€3,500 to €4,500	**0.89**	**41%**	**64.6%**	**35%**	**21.3%**	**61%**	11.8%
	€4,500 to €5,500	**1.03**	**63%**	**71.8%**	**50%**	**27.4%**	**108%**	7.4%
	Over €5,500	**1.09**	**72%**	**71.2%**	**48%**	**31.8%**	**141%**	10.4%
	N/A and Refusal	**0.76**	**21%**	**54.0%**	**13%**	**19.1%**	**45%**	6.8%
Household head age	Household head < 25	**0.15**	**-77%**	**13.9%**	**-71%**	**0.7%**	**-94%**	2.8%
	25 ≤ Household head ≤ 62	**0.62**	**-2%**	**46.1%**	**-4%**	**13.5%**	**2%**	74.5%
	62 < Household head	**0.73**	**16%**	**58.5%**	**22%**	**13.7%**	**4%**	22.7%
Total		0.63		48.0%		13.2%		100%

Table B.9 – Households holding a regular parking space share by socio-economic variables (1/2)

		Average number of car parking space held	Relative deviation from the mean	Car parking space holding rate	Relative deviation from the mean	Multiple car parking space holding rate	Relative deviation from the mean	Household share
Number of workers per household	0	**0.60**	**-5%**	**49.4%**	**3%**	**10.0%**	**-24%**	28.6%
	1	**0.46**	**-27%**	**38.2%**	**-20%**	**6.8%**	**-48%**	39.0%
	2+	**0.86**	**37%**	**58.5%**	**22%**	**23.7%**	**80%**	32.4%
Number of mobility disabled	0	**0.65**	**3%**	**48.8%**	**2%**	**13.8%**	**5%**	87.3%
	1+	**0.52**	**-17%**	**42.5%**	**-11%**	**8.5%**	**-35%**	12.7%
Average number of daily trips per household member	0	**0.71**	**12%**	**51.9%**	**8%**	**16.4%**	**24%**	34.3%
	above 0 to 1	**0.74**	**17%**	**52.7%**	**10%**	**18.1%**	**37%**	20.8%
	above 1 to 2	**0.57**	**-10%**	**45.8%**	**-5%**	**10.0%**	**-24%**	22.7%
	more than 2	**0.47**	**-25%**	**39.9%**	**-17%**	**6.9%**	**-48%**	22.2%
Total		0.63		48.0%		13.2%		100%

Table B.10 – Households holding a regular parking space share by socio-economic variables (2/2)

For household with workers or students		Average number of car parking space held	Relative deviation from the mean	Car parking space holding rate	Relative deviation from the mean	Multiple car parking space holding rate	Relative deviation from the mean	Household share
Households with at list one working/study IAU commune type	Agglomeration center communes	**0.56**	**-10%**	**42.9%**	**-7%**	**11.8%**	**-16%**	35.5%
	In-agglomeration - Dense communes	**0.66**	**6%**	**49.7%**	**7%**	**14.5%**	**3%**	44.4%
	In-agglomeration - Predominantly urbanized communes	**0.83**	**32%**	**55.8%**	**20%**	**23.4%**	**67%**	19.3%
	In-agglomeration - Other communes	**0.96**	**52%**	**61.1%**	**32%**	**28.5%**	**103%**	8.3%
	Out-of-agglomeration - Main communes	**0.99**	**57%**	**61.7%**	**33%**	**31.3%**	**122%**	3.6%
	Out-of-agglomeration - Other communes	**1.12**	**78%**	**64.0%**	**38%**	**40.9%**	**191%**	1.6%
	Rural communes	**1.14**	**82%**	**65.4%**	**41%**	**36.0%**	**156%**	2.1%
	N/A	**0.64**	**3%**	**45.1%**	**-3%**	**15.7%**	**12%**	19.8%
Households with at list one working/study type	Unique out of home	**0.65**	**4%**	**47.8%**	**3%**	**14.9%**	**6%**	87.6%
	Unique at home	**0.72**	**15%**	**48.1%**	**4%**	**19.4%**	**38%**	4.4%
	Not unique	**0.63**	**1%**	**44.8%**	**-3%**	**14.8%**	**5%**	20.9%
	N/A	0.43	-31%	34.1%	-27%	9.1%	-35%	0.1%
Households with at list one working/study	Car parking	**0.73**	**16%**	**52.5%**	**13%**	**17.8%**	**27%**	62.3%
	Bike parking	**0.70**	**12%**	**50.8%**	**9%**	**16.9%**	**20%**	60.1%
Total		0.63		46.4%		14.1%		100%

Table B.11 – Households with at least one worker or student, holding a regular parking space share by socio-economic variables

		Average number of motorcycles	Relative deviation from the mean	Motorcycle holding rate	Relative deviation from the mean	Household share
IAU commune type	Agglomeration center communes	**0.07**	**-28%**	**6.7%**	**-25%**	23.5%
	In-agglomeration - Dense communes	**0.08**	**-15%**	**7.5%**	**-15%**	36.5%
	In-agglomeration - Predominantly urbanized communes	**0.12**	**17%**	**10.4%**	**17%**	22.7%
	In-agglomeration - Other communes	**0.12**	**17%**	**10.4%**	**17%**	7.0%
	Out-of-agglomeration - Main communes	**0.14**	**36%**	**11.5%**	**29%**	4.2%
	Out-of-agglomeration - Other communes	**0.15**	**53%**	**13.7%**	**54%**	2.7%
	Rural communes	**0.22**	**122%**	**18.3%**	**106%**	3.4%
Housing type	Other	0.07	-35%	6.5%	-26%	0.2%
	Collective housing	**0.07**	**-30%**	**6.6%**	**-26%**	72.4%
	Individual Housing	**0.18**	**78%**	**15.0%**	**69%**	27.4%
Housing surface	Under 50 m²	**0.05**	**-46%**	**5.1%**	**-43%**	4.3%
	51m² to 70m²	**0.08**	**-23%**	**7.3%**	**-18%**	13.8%
	71m² to 90m²	**0.10**	**2%**	**9.1%**	**3%**	21.1%
	91m² to 110m²	**0.15**	**45%**	**12.0%**	**35%**	21.4%
	111m² to 150m²	**0.18**	**75%**	**14.4%**	**62%**	24.5%
	151m² and over	**0.19**	**95%**	**17.9%**	**101%**	14.6%
	N/A	0.05	-46%	5.4%	-39%	0.2%
Household monthly income	€800 to €1,200	**0.02**	**-76%**	**2.3%**	**-74%**	10.4%
	€1,200 to €1,600	**0.04**	**-59%**	**3.9%**	**-56%**	10.5%
	€1,600 to €2,000	**0.05**	**-48%**	**4.8%**	**-46%**	11.3%
	€2,000 to €2,400	**0.06**	**-41%**	**5.5%**	**-38%**	10.3%
	€2,400 to €3,000	**0.09**	**-6%**	**8.6%**	**-3%**	11.8%
	€3,000 to €3,500	**0.13**	**29%**	**10.9%**	**23%**	9.4%
	€3,500 to €4,500	**0.15**	**53%**	**14.0%**	**58%**	11.8%
	€4,500 to €5,500	**0.16**	**61%**	**14.1%**	**58%**	7.4%
	Over €5,500	**0.22**	**115%**	**17.7%**	**100%**	10.4%
	N/A and Refusal	**0.23**	**133%**	**22.6%**	**154%**	6.8%
Household head age	Household head < 25	**0.05**	**-54%**	**4.3%**	**-52%**	2.8%
	25 ≤ Household head ≤ 62	**0.13**	**26%**	**11.2%**	**26%**	74.5%
	62 < Household head	**0.02**	**-78%**	**1.9%**	**-78%**	22.7%
Number of workers per household	0	**0.02**	**-81%**	**1.9%**	**-79%**	28.6%
	1	**0.09**	**-12%**	**8.0%**	**-10%**	39.0%
	2+	**0.19**	**86%**	**16.2%**	**82%**	32.4%
Number of mobility disabled	0	**0.11**	**6%**	**9.5%**	**6%**	87.3%
	1+	**0.06**	**-43%**	**4.9%**	**-45%**	12.7%
Average number of daily trips per household member	0	**0.10**	**-2%**	**8.6%**	**-3%**	34.3%
	above 0 to 1	**0.13**	**30%**	**11.6%**	**30%**	20.8%
	above 1 to 2	**0.11**	**7%**	**9.4%**	**6%**	22.7%
	more than 2	**0.07**	**-32%**	**6.3%**	**-29%**	22.2%
Total		0.10		8.9%		100%

Table B.12 – Households holding a motorcycle share by socio-economic variables

For household with workers or students		Average number of motorcycles	Relative deviation from the mean	Motorcycle holding rate	Relative deviation from the mean	Household share
Households with at list one working/study IAU commune type	Agglomeration center communes	**0.13**	**4%**	**11.9%**	**5%**	35.5%
	In-agglomeration - Dense communes	**0.14**	**7%**	**12.0%**	**5%**	44.4%
	In-agglomeration - Predominantly urbanized communes	**0.14**	**12%**	**12.6%**	**10%**	19.3%
	In-agglomeration - Other communes	**0.13**	**-1%**	**11.0%**	**-4%**	8.3%
	Out-of-agglomeration - Main communes	**0.22**	**71%**	**18.5%**	**62%**	3.6%
	Out-of-agglomeration - Other communes	**0.18**	**39%**	**15.0%**	**32%**	1.6%
	Rural communes	**0.22**	**71%**	**18.7%**	**64%**	2.1%
	N/A	**0.14**	**8%**	**12.6%**	**10%**	19.8%
Households with at list one working/study type	Unique out of home	**0.13**	**1%**	**11.5%**	**0%**	87.6%
	Unique at home	**0.18**	**37%**	**16.1%**	**41%**	4.4%
	Not unique	**0.14**	**5%**	**12.4%**	**9%**	20.9%
	N/A	**0.18**	**37%**	**17.7%**	**55%**	0.1%
Households with at list one working/study	Car parking	**0.15**	**13%**	**12.7%**	**11%**	62.3%
	Bike parking	**0.15**	**14%**	**12.9%**	**13%**	60.1%
Total		0.13		11.4%		100%

Table B.13 – Households with at least one worker or student, holding a motorcycle share by socio-economic variables

		Average number of bikes	Relative deviation from the mean	Bike holding rate	Relative deviation from the mean	Multiple bike holding rate	Relative deviation from the mean	Household share
IAU commune type	Agglomeration center communes	0.52	-52%	29.0%	-39%	13.2%	-56%	23.4%
	In-agglomeration - Dense communes	0.93	-14%	44.7%	-7%	25.5%	-16%	36.6%
	In-agglomeration - Predominantly urbanized communes	1.38	28%	58.6%	22%	39.8%	32%	22.6%
	In-agglomeration - Other communes	1.66	54%	64.9%	35%	47.6%	58%	7.0%
	Out-of-agglomeration - Main communes	1.54	43%	60.5%	26%	43.3%	44%	4.2%
	Out-of-agglomeration - Other communes	1.94	80%	71.0%	48%	54.0%	79%	2.7%
	Rural communes	2.13	97%	74.1%	54%	60.8%	102%	3.4%
Housing type	Other	0.96	-11%	40.4%	-16%	24.0%	-20%	0.4%
	Collective housing	0.74	-31%	39.2%	-18%	20.6%	-32%	72.4%
	Individual Housing	1.97	83%	71.4%	49%	55.6%	84%	27.2%
Housing surface	Under 50 m²	0.36	-67%	26.0%	-46%	7.3%	-76%	27.0%
	51m² to 70m²	0.79	-27%	44.0%	-8%	22.9%	-24%	24.5%
	71m² to 90m²	1.23	14%	54.7%	14%	36.3%	21%	21.2%
	91m² to 110m²	1.68	55%	62.8%	31%	48.2%	60%	11.7%
	111m² to 150m²	2.07	92%	70.3%	47%	57.2%	90%	10.4%
	151m² and over	2.38	120%	78.1%	63%	65.4%	117%	4.9%
	N/A	0.76	-30%	36.5%	-24%	22.9%	-24%	0.3%
Household monthly income	€800 to €1,200	0.39	-64%	26.5%	-45%	9.1%	-70%	10.4%
	€1,200 to €1,600	0.51	-53%	31.1%	-35%	13.1%	-56%	10.5%
	€1,600 to €2,000	0.65	-39%	38.0%	-21%	16.3%	-46%	11.3%
	€2,000 to €2,400	0.83	-23%	43.1%	-10%	22.9%	-24%	10.3%
	€2,400 to €3,000	1.01	-6%	48.3%	1%	29.0%	-4%	11.8%
	€3,000 to €3,500	1.22	13%	53.3%	11%	35.3%	17%	9.4%
	€3,500 to €4,500	1.58	46%	62.8%	31%	45.5%	51%	11.8%
	€4,500 to €5,500	1.83	70%	66.6%	39%	52.4%	74%	7.4%
	Over €5,500	1.90	76%	67.9%	42%	53.6%	78%	10.4%
	N/A and Refusal	1.08	0%	46.6%	-3%	30.6%	2%	6.8%
Household head age	Household head < 25	0.24	-78%	18.5%	-61%	5.4%	-82%	2.8%
	25 ≤ Household head ≤ 62	1.27	18%	54.2%	13%	35.6%	18%	74.5%
	62 < Household head	0.55	-49%	31.3%	-35%	15.4%	-49%	22.7%
Number of individuals over 5	1	0.36	-67%	27.6%	-43%	5.8%	-81%	36.3%
	2	0.92	-15%	48.3%	1%	30.0%	0%	35.3%
	3	1.71	59%	68.5%	43%	52.8%	75%	13.3%
	4+	2.62	143%	78.1%	63%	68.8%	128%	15.1%
Number of mobility disabled	0	1.13	5%	49.8%	4%	31.5%	5%	87.3%
	1+	0.72	-34%	35.2%	-27%	20.6%	-32%	12.7%
Average number of daily trips per household member	0	0.94	-12%	45.7%	-5%	26.4%	-12%	34.3%
	above 0 to 1	1.42	31%	56.0%	17%	40.4%	34%	20.8%
	above 1 to 2	1.12	4%	48.7%	2%	30.9%	2%	22.7%
	more than 2	0.93	-14%	43.2%	-10%	25.4%	-16%	22.2%
Total		1.08		48.0%		30.1%		100%

Table B.14 – Households holding a bike share by socio-economic variables

For household with workers or students		Average number of bikes	Relative deviation from the mean	Bike holding rate	Relative deviation from the mean	Multiple bike holding rate	Relative deviation from the mean	Household share
Households with at list one working/study IAU commune type	Agglomeration center communes	1.17	-8%	49.6%	-8%	32.2%	-9%	35.5%
	In-agglomeration - Dense communes	1.36	8%	56.7%	5%	38.3%	8%	44.4%
	In-agglomeration - Predominantly urbanized communes	1.73	37%	66.8%	24%	49.6%	40%	19.3%
	In-agglomeration - Other communes	1.73	36%	65.2%	21%	47.7%	35%	8.3%
	Out-of-agglomeration - Main communes	2.02	60%	74.0%	37%	56.6%	60%	3.6%
	Out-of-agglomeration - Other communes	2.10	66%	74.0%	37%	57.1%	62%	1.6%
	Rural communes	2.04	61%	72.1%	34%	55.3%	56%	2.1%
	N/A	1.37	8%	55.5%	3%	38.6%	9%	19.8%
Households with at list one working/study type	Unique out of home	1.31	3%	55.0%	2%	36.5%	3%	87.6%
	Unique at home	1.56	23%	59.5%	10%	41.0%	16%	4.4%
	Not unique	1.33	5%	55.0%	2%	37.5%	6%	20.9%
	N/A	1.23	-3%	69.7%	29%	45.0%	27%	0.1%
Households with at list one	Car parking	1.46	15%	58.8%	9%	41.0%	16%	62.3%
	Bike parking	1.45	14%	58.8%	9%	40.6%	15%	60.1%
Total		1.26		53.9%		35.3%		100%

Table B.15 – Households with at least one worker or student, holding a bike share by socio-economic variables

		Individuals (>3) with PT pass rate	Relative deviation from the mean	Individual (>3) share
IAU commune type	Agglomeration center communes	**50.2%**	**43%**	19.2%
	In-agglomeration - Dense communes	**37.2%**	**6%**	37.0%
	In-agglomeration - Predominantly urbanized communes	**29.8%**	**-15%**	24.4%
	In-agglomeration - Other communes	**25.6%**	**-27%**	7.9%
	Out-of-agglomeration - Main communes	**24.0%**	**-32%**	4.5%
	Out-of-agglomeration - Other communes	**18.2%**	**-48%**	3.1%
	Rural communes	**18.2%**	**-48%**	3.9%
Housing type	Other	24.5%	-30%	0.1%
	Collective housing	**40.5%**	**16%**	67.9%
	Individual Housing	**23.5%**	**-33%**	32.0%
Housing surface	Under 50 m²	**52.9%**	**51%**	18.6%
	51m² to 70m²	**36.7%**	**5%**	22.8%
	71m² to 90m²	**31.9%**	**-9%**	24.6%
	91m² to 110m²	**28.2%**	**-20%**	14.4%
	111m² to 150m²	**25.4%**	**-27%**	12.8%
	151m² and over	**24.0%**	**-32%**	6.5%
	N/A	32.8%	-6%	0.3%
Household monthly income	Less than €1,200	**51.3%**	**46%**	8.6%
	€1,200 to €1,600	**41.5%**	**19%**	9.1%
	€1,600 to €2,000	**36.3%**	**4%**	9.6%
	€2,000 to €2,400	**34.5%**	**-1%**	9.2%
	€2,400 to €3,000	**31.1%**	**-11%**	11.5%
	€3,000 to €3,500	**30.8%**	**-12%**	10.0%
	€3,500 to €4,500	**32.2%**	**-8%**	13.3%
	€4,500 to €5,500	**31.8%**	**-9%**	8.6%
	Over €5,500	**33.3%**	**-5%**	13.1%
	N/A and Refusal	**30.5%**	**-13%**	7.0%
Household head age	Household head < 25	**67.0%**	**91%**	1.8%
	25 ≤ Household head ≤ 62	**36.7%**	**5%**	81.0%
	62 < Household head	**23.8%**	**-32%**	17.2%
Number of individuals (>5) per household	1	**44.6%**	**27%**	17.4%
	2	**32.8%**	**-6%**	33.7%
	3	**33.2%**	**-5%**	18.7%
	4 and over	**33.1%**	**-5%**	30.2%
	Total	35.0%		100%

Table B.16 – Individuals over 3 holding a PT pass share by socio-economic variables (1/3)

		Individuals (>3) with PT pass rate	Relative deviation from the mean	Individual (>3) share
Age	4 to 14	**13.6%**	**-61%**	15.5%
	15 to 24	**66.4%**	**90%**	11.3%
	25 to 34	**46.2%**	**32%**	15.3%
	35 to 54	**37.6%**	**7%**	32.8%
	55 to 64	**24.9%**	**-29%**	12.2%
	65 to 74	**20.3%**	**-42%**	6.8%
	75 an above	**25.7%**	**-27%**	6.0%
Mobility disabled	Yes	**33.1%**	**-6%**	7.9%
	No	**36.1%**	**3%**	88.2%
	N/A	**15.2%**	**-57%**	3.9%
Gender	Man	**33.5%**	**-4%**	47.7%
	Woman	**36.4%**	**4%**	52.3%
Highest level of education	Never attended school	**49.0%**	**40%**	0.7%
	Currently studying	**39.0%**	**11%**	22.7%
	Primary school	**29.2%**	**-17%**	4.4%
	Secondary school	**34.4%**	**-2%**	6.3%
	High school	**27.7%**	**-21%**	16.8%
	High school degree	**34.0%**	**-3%**	8.8%
	Apprenticeship and other higher education	25.6%	-27%	0.4%
	Higher education	**35.4%**	**1%**	10.8%
	Bachelor degree and over	**39.6%**	**13%**	27.0%
	N/A	**3.9%**	**-89%**	2.0%
Occupation	Worker	**41.5%**	**18%**	47.4%
	+Full-time job	***41.4%***	***18%***	*42.5%*
	+Part-time job	***42.4%***	***21%***	*5.0%*
	Retired	**20.0%**	**-43%**	16.0%
	Homemaker	**18.6%**	**-47%**	4.8%
	Unemployed	**33.8%**	**-3%**	5.5%
	Student	**39.1%**	**12%**	22.5%
	Inactive and N/A	**16.1%**	**-54%**	3.7%
Socio-professional category	No professional activity	**39.1%**	**12%**	22.4%
	Farmer	29.3%	-16%	0.1%
	Employee	**44.5%**	**27%**	14.1%
	Blue-collar worker	**35.1%**	**0%**	8.0%
	Intermediate profession	**39.9%**	**14%**	13.9%
	Craftsman, Retailer and Business leader	**13.5%**	**-61%**	2.3%
	Executive and Intellectual profession	**44.9%**	**28%**	14.3%
	Retired	**20.0%**	**-43%**	16.0%
	N/A	**19.0%**	**-46%**	9.0%
Total		35.0%		100%

Table B.17 – Individuals over 3 holding a PT pass share by socio-economic variables (2/3)

		Individuals (>3) with PT pass rate	Relative deviation from the mean	Individual (>3) share
PT pass deduction	Aware of it	100.0%	186%	29.1%
	Unkown and N/A	8.3%	-76%	70.9%
Number of daily trips made	Less than 2	40.8%	17%	29.6%
	3	39.7%	13%	10.0%
	4	36.8%	5%	21.0%
	5	36.6%	4%	9.1%
	6	32.2%	-8%	9.4%
	7 and above	26.7%	-24%	12.3%
	N/A	18.5%	-47%	8.5%
	Total	35.0%		100%

Table B.18 – Individuals over 3 holding a PT pass share by socio-economic variables (3/3)

For workers and students		Individuals (>3) with PT pass rate	Relative deviation from the mean	Population (>3) share
Workplace location IAU commune type	Agglomeration center communes	72.5%	78%	19.8%
	In-agglomeration - Dense communes	46.8%	15%	24.8%
	In-agglomeration - Predominantly urbanized communes	22.6%	-44%	10.6%
	In-agglomeration - Other communes	16.2%	-60%	4.4%
	Out-of-agglomeration - Main communes	10.5%	-74%	1.9%
	Out-of-agglomeration - Other communes	8.5%	-79%	0.8%
	Rural communes	8.5%	-79%	1.1%
	N/A	30.9%	-24%	36.5%
Unicity of workplace location	Yes, out of home	47.4%	16%	80.8%
	Yes, home	15.1%	-63%	3.5%
	No	39.8%	-2%	15.6%
Car parking available at work/study	Yes	37.4%	-8%	38.0%
	No	64.5%	58%	22.1%
	N/A	30.7%	-25%	40.0%
Bike parking available at work/study	Yes	41.5%	2%	36.5%
	No	56.5%	39%	23.6%
	N/A	30.7%	-25%	39.9%
	Total	40.7%		100%

Table B.19 – Workers and students over 3 holding a PT pass share by socio-economic variables

		Individuals (>13) with bike-sharing subscription rate	Relative deviation from the mean	Individual (>13) share
IAU commune type	Agglomeration center communes	**10.3%**	**282%**	20.0%
	In-agglomeration - Dense communes	**1.3%**	**-53%**	36.8%
	In-agglomeration - Predominantly urbanized communes	**0.4%**	**-87%**	24.2%
	In-agglomeration - Other communes	**0.2%**	**-93%**	7.8%
	Out-of-agglomeration - Main communes	**1.2%**	**-57%**	4.4%
	Out-of-agglomeration - Other communes	**0.1%**	**-95%**	3.0%
	Rural communes	**0.3%**	**-88%**	3.9%
Housing type	Other	0.6%	-77%	0.2%
	Collective housing	**3.7%**	**37%**	68.4%
	Individual Housing	**0.6%**	**-79%**	31.4%
Housing surface	Under 50 m²	**4.8%**	**79%**	20.3%
	51m² to 70m²	**2.5%**	**-9%**	23.0%
	71m² to 90m²	**2.0%**	**-27%**	23.7%
	91m² to 110m²	**2.0%**	**-27%**	13.8%
	111m² to 150m²	**2.2%**	**-18%**	12.4%
	151m² and over	**2.2%**	**-20%**	6.5%
	N/A	0.0%	-100%	0.3%
Household monthly income	Less than €1,200	**1.4%**	**-49%**	9.0%
	€1,200 to €1,600	**1.3%**	**-51%**	9.1%
	€1,600 to €2,000	**1.8%**	**-32%**	9.7%
	€2,000 to €2,400	**1.7%**	**-36%**	9.2%
	€2,400 to €3,000	**2.4%**	**-10%**	11.6%
	€3,000 to €3,500	**1.8%**	**-35%**	10.0%
	€3,500 to €4,500	**3.1%**	**13%**	13.1%
	€4,500 to €5,500	**4.1%**	**51%**	8.3%
	Over €5,500	**5.9%**	**119%**	12.8%
	N/A and Refusal	**2.3%**	**-16%**	7.2%
Household head age	Household head < 25	**3.5%**	**30%**	2.1%
	25 ≤ Household head ≤ 62	**3.1%**	**16%**	78.0%
	62 < Household head	**0.9%**	**-68%**	19.9%
Number of individuals per household	1	**3.7%**	**38%**	19.6%
	2	**2.8%**	**5%**	29.8%
	3	**2.5%**	**-7%**	18.4%
	4 and over	**2.1%**	**-24%**	32.2%
	Total	**2.7%**		100%

Table B.20 – Individuals over 13 holding a bike sharing subscription share by socio-economic variables (1/3)

		Individuals (>13) with bike-sharing subscription rate	Relative deviation from the mean	Individual (>13) share
Age	13 to 14	**0.6%**	**-78%**	1.5%
	15 to 24	**1.9%**	**-30%**	13.2%
	25 to 34	**4.7%**	**73%**	17.8%
	35 to 54	**3.1%**	**16%**	38.2%
	55 to 64	**2.2%**	**-17%**	14.3%
	65 to 74	**0.9%**	**-68%**	7.9%
	75 an above	**0.4%**	**-87%**	7.0%
Mobility disabled	Yes	**1.0%**	**-64%**	8.9%
	No	**2.9%**	**8%**	89.8%
	N/A	**0.3%**	**-91%**	1.3%
Gender	Man	**3.5%**	**30%**	47.2%
	Woman	**2.0%**	**-27%**	52.8%
Highest level of education	Never attended school	**0.0%**	**-100%**	0.8%
	Currently studying	**2.4%**	**-13%**	11.9%
	Primary school	**0.1%**	**-96%**	5.2%
	Secondary school	**0.2%**	**-94%**	7.3%
	High school	**0.4%**	**-84%**	19.6%
	High school degree	**1.5%**	**-46%**	10.3%
	Apprenticeship and other higher education	**3.3%**	**23%**	0.5%
	Higher education	**2.1%**	**-22%**	12.6%
	Bachelor degree and over	**6.0%**	**122%**	31.5%
	N/A	0.0%	-100%	0.3%
Occupation	Worker	**3.8%**	**41%**	55.3%
	+Full-time job	**3.9%**	***46%***	*49.5%*
	+Part-time job	**2.7%**	***-1%***	*5.8%*
	Retired	**0.8%**	**-72%**	18.7%
	Homemaker	**1.1%**	**-60%**	5.6%
	Unemployed	**1.7%**	**-37%**	6.4%
	Student	**2.1%**	**-22%**	11.7%
	Inactive and N/A	**1.6%**	**-39%**	2.3%
Socio-professional category	No professional activity	**2.1%**	**-21%**	11.7%
	Farmer	0.0%	-100%	0.1%
	Employee	**1.4%**	**-50%**	16.4%
	Blue-collar worker	**0.8%**	**-71%**	9.3%
	Intermediate profession	**3.0%**	**11%**	16.2%
	Craftsman, Retailer and Business leader	**3.9%**	**44%**	2.7%
	Executive and Intellectual profession	**7.9%**	**194%**	16.7%
	Retired	**0.8%**	**-72%**	18.6%
	N/A	**1.2%**	**-54%**	8.4%
Total		**2.7%**		100%

Table B.21 – Individuals over 13 holding a bike sharing subscription share by socio-economic variables (2/3)

		Individuals (>13) with bike-sharing subscription rate	Relative deviation from the mean	Individual (>13) share
PT pass deduction	Aware of it	**4.8%**	**78%**	32.7%
	Unkown and N/A	**1.7%**	**-38%**	67.3%
Number of daily trips made	Less than 2	**2.0%**	**-27%**	28.5%
	3	**3.3%**	**21%**	10.2%
	4	**2.9%**	**8%**	20.6%
	5	**3.6%**	**33%**	9.7%
	6	**3.7%**	**35%**	9.9%
	7 and above	**3.2%**	**19%**	13.7%
	N/A	**0.7%**	**-72%**	7.3%
Total		**2.7%**		100%

Table B.22 – Individuals over 13 holding a bike sharing subscription share by socio-economic variables (3/3)

For workers and students		Individuals (>13) with bike-sharing subscription rate	Relative deviation from the mean	Individual (>13) share
Workplace location IAU commune type	Agglomeration center communes	**7.8%**	**121%**	24.1%
	In-agglomeration - Dense communes	**3.1%**	**-12%**	30.1%
	In-agglomeration - Predominantly urbanized communes	**1.4%**	**-60%**	12.9%
	In-agglomeration - Other communes	**0.6%**	**-84%**	5.3%
	Out-of-agglomeration - Main communes	**0.9%**	**-76%**	2.3%
	Out-of-agglomeration - Other communes	**0.3%**	**-91%**	1.0%
	Rural communes	**1.2%**	**-67%**	1.4%
	N/A	**2.1%**	**-41%**	22.9%
Unicity of workplace location	Yes, out of home	**4.0%**	**13%**	73.3%
	Yes, home	**3.8%**	**7%**	3.0%
	No	**3.0%**	**-15%**	14.0%
	N/A	**0.8%**	**-77%**	9.7%
Car parking available at work/study	Yes	**3.4%**	**-5%**	46.2%
	No	**5.0%**	**43%**	26.8%
	N/A	**2.3%**	**-35%**	27.0%
Bike parking available at work/study	Yes	**3.7%**	**5%**	44.3%
	No	**4.4%**	**26%**	28.6%
	N/A	**2.3%**	**-35%**	27.0%
Total		**3.5%**		100%

Table B.23 – Workers and students over 13 holding a bike sharing subscription share by socio-economic variables

B.2 Subpopulation socio-economic variables data

		Adults with a driving license share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	**82.4%**	**1%**	32.6%
	In-agglomeration - Dense communes	**79.1%**	**-3%**	36.2%
	In-agglomeration - Predominantly urbanized communes	**83.0%**	**2%**	19.3%
	In-agglomeration - Other communes	**85.4%**	**5%**	4.8%
	Out-of-agglomeration - Main communes	**81.1%**	**-1%**	3.6%
	Out-of-agglomeration - Other communes	**86.0%**	**5%**	1.7%
	Rural communes	**94.6%**	**16%**	1.8%
Housing type	Other	76.2%	-7%	0.4%
	Collective housing	**80.8%**	**-1%**	86.4%
	Individual Housing	**87.4%**	**7%**	13.3%
Housing surface	Under 30 m²	**71.5%**	-21%	19.8%
	31m² to 40m²	**81.8%**	**-12%**	15.7%
	41m² to 50m²	**80.5%**	**0%**	16.6%
	51m² to 60m²	**84.2%**	**-1%**	13.0%
	61m² to 80m²	**84.7%**	**3%**	19.9%
	81m² and over	**90.4%**	**4%**	14.8%
	N/A	64.4%	**11%**	0.3%
Household monthly income	Less than €800	**57.7%**	**-29%**	8.5%
	€800 to €1,200	**62.9%**	**-23%**	13.3%
	€1,200 to €1,600	**73.6%**	**-10%**	17.7%
	€1,600 to €2,000	**88.8%**	**9%**	17.6%
	€2,000 to €2,400	**92.0%**	**13%**	13.0%
	€2,400 to €3,000	**94.3%**	**15%**	10.9%
	€3,000 to €3,500	**95.4%**	**17%**	5.5%
	€3,500 to €4,500	**93.8%**	**15%**	4.0%
	Over €4,500	**98.3%**	**20%**	3.6%
	N/A and Refusal	**83.7%**	**2%**	5.9%
	Total	81.7%		100%

Table B.24 – Adults holding a driving license subpopulation share by socio-economic variables (1/3)

		Adults with a driving license share	Relative deviation from the mean	Adult share
Age	18 to 25	68.6%	-16%	7.3%
	26 to 35	82.5%	1%	16.7%
	36 to 45	80.8%	-1%	13.8%
	46 to 55	83.7%	3%	15.6%
	56 to 65	86.5%	6%	19.2%
	66 to 75	82.1%	1%	11.9%
	76 an above	79.2%	-3%	15.4%
Mobility disabled	Yes	71.7%	-12%	15.2%
	No	83.4%	2%	84.2%
	N/A	85.6%	5%	0.6%
Gender	Man	85.4%	5%	43.6%
	Woman	78.7%	-4%	56.4%
Highest level of education	Never attended school	14.6%	-82%	0.3%
	Currently studying	66.7%	-18%	4.7%
	Primary school	56.0%	-31%	6.5%
	Secondary school	66.1%	-19%	7.8%
	High school	78.7%	-4%	18.4%
	High school degree	81.1%	-1%	10.6%
	Apprenticeship and other higher education	82.3%	1%	0.5%
	Higher education	87.9%	8%	13.5%
	Bachelor degree and over	91.1%	12%	37.3%
	N/A	83.5%	2%	0.4%
Occupation	Worker	84.8%	4%	51.3%
	+Full-time job	*85.5%*	*5%*	*47.4%*
	+Part-time job	*76.4%*	*-6%*	*3.9%*
	Retired	81.7%	0%	33.7%
	Homemaker	76.9%	-6%	1.4%
	Unemployed	74.7%	-9%	6.2%
	Student	66.0%	-19%	4.6%
	Inactive and N/A	67.7%	-17%	2.9%
Socio-professional category	No professional activity	66.1%	-19%	4.5%
	Farmer	12.4%	-85%	0.1%
	Blue-collar worker	76.7%	-6%	13.5%
	Worker	71.8%	-12%	6.6%
	Intermediate profession	84.7%	4%	17.0%
	Craftsman, Retailer and Business leader	92.8%	14%	2.0%
	Executive and Intellectual profession	91.6%	12%	18.3%
	Retired	81.7%	0%	33.6%
	N/A	70.0%	-14%	4.3%
Total		81.7%		100%

Table B.25 – Adults holding a driving license subpopulation share by socio-economic variables (2/3)

		Adults with a driving license share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	75.2%	-8%	33.5%
	Unkown and N/A	84.9%	4%	66.5%
Number of daily trips made	Less than 2	78.5%	-4%	27.3%
	3	83.0%	2%	12.6%
	4	85.5%	5%	21.4%
	5	83.5%	2%	11.6%
	6	84.6%	4%	10.0%
	7 and above	84.1%	3%	11.6%
	N/A	64.4%	-21%	5.4%
Total		81.7%		100%

Table B.26 – Adults holding a driving license subpopulation share by socio-economic variables (3/3)

For workers and students		Adults with a driving license share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	81.3%	-2%	31.5%
	In-agglomeration - Dense communes	81.9%	-2%	34.5%
	In-agglomeration - Predominantly urbanized communes	87.3%	5%	10.9%
	In-agglomeration - Other communes	90.1%	8%	5.5%
	Out-of-agglomeration - Main communes	90.9%	9%	1.4%
	Out-of-agglomeration - Other communes	91.5%	10%	0.6%
	Rural communes	93.4%	12%	1.0%
	N/A	83.1%	0%	14.4%
Unicity of workplace location	Yes, out of home	83.4%	0%	81.2%
	Yes, home	76.9%	-8%	2.9%
	No	83.6%	0%	15.8%
Car parking available at work/study	Yes	86.3%	4%	51.2%
	No	78.8%	-5%	29.9%
	N/A	82.0%	-1%	19.0%
Bike parking available at work/study	Yes	85.2%	2%	50.6%
	No	80.8%	-3%	30.4%
	N/A	82.0%	-1%	19.0%
Total		83.2%		100%

Table B.27 – Worker or student adults holding a driving license subpopulation share by socio-economic variables

		Adults with a car share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	**28.1%**	**-43%**	32.6%
	In-agglomeration - Dense communes	**50.8%**	**2%**	36.2%
	In-agglomeration - Predominantly urbanized communes	**69.7%**	**40%**	19.3%
	In-agglomeration - Other communes	**69.3%**	**39%**	4.8%
	Out-of-agglomeration - Main communes	**69.7%**	**40%**	3.6%
	Out-of-agglomeration - Other communes	**79.3%**	**60%**	1.7%
	Rural communes	**82.3%**	**66%**	1.8%
Housing type	Other	52.9%	6%	0.4%
	Collective housing	**45.8%**	**-8%**	86.4%
	Individual Housing	**74.8%**	**51%**	13.3%
Housing surface	Under 30 m²	**25.9%**	**-48%**	19.8%
	31m² to 40m²	**37.5%**	**-25%**	15.7%
	41m² to 50m²	**48.0%**	-3%	16.6%
	51m² to 60m²	**56.1%**	**13%**	13.0%
	61m² to 80m²	**60.0%**	**21%**	19.9%
	81m² and over	**77.1%**	**55%**	14.8%
	N/A	34.1%	-31%	0.3%
Household monthly income	Less than €800	**16.2%**	**-67%**	8.5%
	€800 to €1,200	**30.9%**	**-38%**	13.3%
	€1,200 to €1,600	**41.6%**	**-16%**	17.7%
	€1,600 to €2,000	**57.7%**	**16%**	17.6%
	€2,000 to €2,400	**60.3%**	**21%**	13.0%
	€2,400 to €3,000	**62.0%**	**25%**	10.9%
	€3,000 to €3,500	**64.9%**	**31%**	5.5%
	€3,500 to €4,500	**67.3%**	**36%**	4.0%
	Over €4,500	**77.8%**	**57%**	3.6%
	N/A and Refusal	**50.6%**	**2%**	5.9%
	Total	49.7%		100%

Table B.28 – Adults holding a car subpopulation share by socio-economic variables (1/3)

		Adults with a car share	Relative deviation from the mean	Adult share
Age	18 to 25	**28.8%**	**-42%**	7.3%
	26 to 35	**41.8%**	**-16%**	16.7%
	36 to 45	**51.3%**	**3%**	13.8%
	46 to 55	**54.3%**	**9%**	15.6%
	56 to 65	**60.7%**	**22%**	19.2%
	66 to 75	**60.1%**	**21%**	11.9%
	76 an above	**40.1%**	**-19%**	15.4%
Mobility disabled	Yes	**36.2%**	**-27%**	15.2%
	No	**52.0%**	**5%**	84.2%
	N/A	**62.2%**	**25%**	0.6%
Gender	Man	**54.3%**	**9%**	43.6%
	Woman	**46.1%**	**-7%**	56.4%
Highest level of education	Never attended school	5.6%	-89%	0.3%
	Currently studying	**14.5%**	**-71%**	4.7%
	Primary school	**31.5%**	**-37%**	6.5%
	Secondary school	**38.3%**	**-23%**	7.8%
	High school	**53.7%**	**8%**	18.4%
	High school degree	**56.8%**	**14%**	10.6%
	Apprenticeship and other higher education	**42.1%**	**-15%**	0.5%
	Higher education	**59.8%**	**20%**	13.5%
	Bachelor degree and over	**52.5%**	**6%**	37.3%
	N/A	42.2%	-15%	0.4%
Occupation	Worker	**53.5%**	**8%**	51.3%
	+Full-time job	***54.2%***	***9%***	*47.4%*
	+Part-time job	***43.9%***	***-12%***	*3.9%*
	Retired	**52.0%**	**5%**	33.7%
	Homemaker	**39.1%**	**-21%**	1.4%
	Unemployed	**37.5%**	**-25%**	6.2%
	Student	**14.6%**	**-71%**	4.6%
	Inactive and N/A	**42.4%**	**-15%**	2.9%
Socio-professional category	No professional activity	**14.6%**	**-71%**	4.5%
	Farmer	12.4%	-75%	0.1%
	Blue-collar worker	**46.7%**	**-6%**	13.5%
	Worker	**50.0%**	**1%**	6.6%
	Intermediate profession	**52.7%**	**6%**	17.0%
	Craftsman, Retailer and Business leader	**74.4%**	**50%**	2.0%
	Executive and Intellectual profession	**52.9%**	**6%**	18.3%
	Retired	**51.9%**	**5%**	33.6%
	N/A	**41.3%**	**-17%**	4.3%
Total		**49.7%**		100%

Table B.29 – Adults holding a car subpopulation share by socio-economic variables (2/3)

		Adults with a car share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	27.9%	-44%	33.5%
	Unkown and N/A	60.7%	22%	66.5%
Number of daily trips made	Less than 2	47.7%	-4%	27.3%
	3	52.7%	6%	12.6%
	4	48.6%	-2%	21.4%
	5	52.4%	5%	11.6%
	6	48.7%	-2%	10.0%
	7 and above	58.2%	17%	11.6%
	N/A	34.5%	-30%	5.4%
Total		49.7%		100%

Table B.30 – Adults holding a car subpopulation share by socio-economic variables (3/3)

For workers and students		Adults with a car share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	36.5%	-27%	31.5%
	In-agglomeration - Dense communes	50.7%	1%	34.5%
	In-agglomeration - Predominantly urbanized communes	69.0%	37%	10.9%
	In-agglomeration - Other communes	80.0%	59%	5.5%
	Out-of-agglomeration - Main communes	84.7%	68%	1.4%
	Out-of-agglomeration - Other communes	91.5%	82%	0.6%
	Rural communes	89.3%	78%	1.0%
	N/A	46.0%	-9%	14.4%
Unicity of workplace location	Yes, out of home	51.1%	2%	81.2%
	Yes, home	44.4%	-12%	2.9%
	No	47.5%	-6%	15.8%
Car parking available at work/study	Yes	59.6%	19%	51.2%
	No	36.6%	-27%	29.9%
	N/A	46.7%	-7%	19.0%
Bike parking available at work/study	Yes	56.0%	11%	50.6%
	No	43.1%	-14%	30.4%
	N/A	46.7%	-7%	19.0%
Total		50.3%		100%

Table B.31 – Worker or student adults holding a car subpopulation share by socio-economic variables

		Adults with a parking space share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	**17.2%**	**-47%**	32.6%
	In-agglomeration - Dense communes	**31.2%**	**-4%**	36.2%
	In-agglomeration - Predominantly urbanized communes	**48.5%**	**50%**	19.3%
	In-agglomeration - Other communes	**48.7%**	**50%**	4.8%
	Out-of-agglomeration - Main communes	**46.9%**	**45%**	3.6%
	Out-of-agglomeration - Other communes	**59.1%**	**83%**	1.7%
	Rural communes	**60.5%**	**87%**	1.8%
Housing type	Other	26.7%	-18%	0.4%
	Collective housing	**28.7%**	**-11%**	86.4%
	Individual Housing	**56.3%**	**74%**	13.3%
Housing surface	Under 30 m²	**9.1%**	**-72%**	19.8%
	31m² to 40m²	**19.1%**	**-41%**	15.7%
	41m² to 50m²	**30.5%**	**-6%**	16.6%
	51m² to 60m²	**36.2%**	**12%**	13.0%
	61m² to 80m²	**42.6%**	**31%**	19.9%
	81m² and over	**62.8%**	**94%**	14.8%
	N/A	20.9%	-35%	0.3%
Household monthly income	Less than €800	**8.7%**	**-73%**	8.5%
	€800 to €1,200	**15.4%**	**-52%**	13.3%
	€1,200 to €1,600	**21.1%**	**-35%**	17.7%
	€1,600 to €2,000	**36.9%**	**14%**	17.6%
	€2,000 to €2,400	**41.7%**	**29%**	13.0%
	€2,400 to €3,000	**45.5%**	**40%**	10.9%
	€3,000 to €3,500	**48.3%**	**49%**	5.5%
	€3,500 to €4,500	**50.9%**	**57%**	4.0%
	Over €4,500	**60.7%**	**88%**	3.6%
	N/A and Refusal	**35.5%**	**10%**	5.9%
Total		32.4%		100%

Table B.32 – Adults holding a parking space subpopulation share by socio-economic variables (1/3)

		Adults with a parking space share	Relative deviation from the mean	Adult share
Age	18 to 25	**11.8%**	**-63%**	7.3%
	26 to 35	**21.0%**	**-35%**	16.7%
	36 to 45	**28.2%**	**-13%**	13.8%
	46 to 55	**33.6%**	**4%**	15.6%
	56 to 65	**42.8%**	**32%**	19.2%
	66 to 75	**46.7%**	**44%**	11.9%
	76 an above	**32.9%**	**2%**	15.4%
Mobility disabled	Yes	**24.8%**	**-23%**	15.2%
	No	**33.7%**	**4%**	84.2%
	N/A	**44.7%**	**38%**	0.6%
Gender	Man	**34.3%**	**6%**	43.6%
	Woman	**30.9%**	**-4%**	56.4%
Highest level of education	Never attended school	5.6%	-83%	0.3%
	Currently studying	**7.1%**	**-78%**	4.7%
	Primary school	**19.9%**	**-39%**	6.5%
	Secondary school	**23.1%**	**-29%**	7.8%
	High school	**35.3%**	**9%**	18.4%
	High school degree	**36.7%**	**13%**	10.6%
	Apprenticeship and other higher education	**34.7%**	**7%**	0.5%
	Higher education	**38.9%**	**20%**	13.5%
	Bachelor degree and over	**34.8%**	**7%**	37.3%
	N/A	38.0%	17%	0.4%
Occupation	Worker	**31.3%**	**-3%**	51.3%
	+Full-time job	***32.0%***	***-1%***	*47.4%*
	+Part-time job	***22.9%***	***-29%***	*3.9%*
	Retired	**41.3%**	**28%**	33.7%
	Homemaker	**32.0%**	**-1%**	1.4%
	Unemployed	**16.4%**	**-49%**	6.2%
	Student	**7.2%**	**-78%**	4.6%
	Inactive and N/A	**22.4%**	**-31%**	2.9%
Socio-professional category	No professional activity	**7.2%**	**-78%**	4.5%
	Farmer	12.4%	-62%	0.1%
	Blue-collar worker	**25.7%**	**-21%**	13.5%
	Worker	**22.1%**	**-32%**	6.6%
	Intermediate profession	**30.7%**	**-5%**	17.0%
	Craftsman, Retailer and Business leader	**46.6%**	**44%**	2.0%
	Executive and Intellectual profession	**32.6%**	**1%**	18.3%
	Retired	**41.3%**	**27%**	33.6%
	N/A	**25.8%**	**-20%**	4.3%
Total		**32.4%**		100%

Table B.33 – Adults holding a parking space subpopulation share by socio-economic variables (2/3)

		Adults with a parking space share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	**16.5%**	**-49%**	33.5%
	Unkown and N/A	**40.4%**	**25%**	66.5%
Number of daily trips made	Less than 2	**29.7%**	**-8%**	27.3%
	3	**33.1%**	**2%**	12.6%
	4	**31.2%**	**-4%**	21.4%
	5	**36.7%**	**13%**	11.6%
	6	**31.5%**	**-3%**	10.0%
	7 and above	**39.1%**	**21%**	11.6%
	N/A	**27.2%**	**-16%**	5.4%
	Total	**32.4%**		100%

Table B.34 – Adults holding a parking space subpopulation share by socio-economic variables (3/3)

For workers and students		Adults with a parking space share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	**19.4%**	**-34%**	31.5%
	In-agglomeration - Dense communes	**31.0%**	**6%**	34.5%
	In-agglomeration - Predominantly urbanized communes	**38.4%**	**31%**	10.9%
	In-agglomeration - Other communes	**51.5%**	**76%**	5.5%
	Out-of-agglomeration - Main communes	**44.7%**	**52%**	1.4%
	Out-of-agglomeration - Other communes	**56.0%**	**91%**	0.6%
	Rural communes	**48.4%**	**65%**	1.0%
	N/A	**27.3%**	**-7%**	14.4%
Unicity of workplace location	Yes, out of home	**29.7%**	**2%**	81.2%
	Yes, home	**21.5%**	**-27%**	2.9%
	No	**28.5%**	**-3%**	15.8%
Car parking available at work/study	Yes	**35.9%**	**22%**	51.2%
	No	**19.3%**	**-34%**	29.9%
	N/A	**27.3%**	**-7%**	19.0%
Bike parking available at work/study	Yes	**33.7%**	**15%**	50.6%
	No	**23.2%**	**-21%**	30.4%
	N/A	**27.3%**	**-7%**	19.0%
	Total	**29.3%**		100%

Table B.35 – Worker or student adults holding a parking space subpopulation share by socio-economic variables

		Adults with a motorcycle share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	4.0%	-3%	32.6%
	In-agglomeration - Dense communes	3.6%	-12%	36.2%
	In-agglomeration - Predominantly urbanized communes	4.6%	13%	19.3%
	In-agglomeration - Other communes	4.6%	11%	4.8%
	Out-of-agglomeration - Main communes	5.3%	30%	3.6%
	Out-of-agglomeration - Other communes	5.0%	23%	1.7%
	Rural communes	6.3%	54%	1.8%
Housing type	Other	4.8%	17%	0.4%
	Collective housing	3.8%	-7%	86.4%
	Individual Housing	5.9%	43%	13.3%
Housing surface	Under 30 m²	4.0%	-3%	19.8%
	31m² to 40m²	4.6%	11%	15.7%
	41m² to 50m²	4.1%	-2%	16.6%
	51m² to 60m²	4.1%	-1%	13.0%
	61m² to 80m²	4.0%	-2%	19.9%
	81m² and over	4.1%	-1%	14.8%
	N/A	0.0%	-100%	0.3%
Household monthly income	Less than €800	1.1%	-73%	8.5%
	€800 to €1,200	2.0%	-51%	13.3%
	€1,200 to €1,600	4.0%	-3%	17.7%
	€1,600 to €2,000	4.4%	6%	17.6%
	€2,000 to €2,400	5.0%	21%	13.0%
	€2,400 to €3,000	4.3%	4%	10.9%
	€3,000 to €3,500	5.6%	36%	5.5%
	€3,500 to €4,500	10.5%	156%	4.0%
	Over €4,500	7.1%	72%	3.6%
	N/A and Refusal	2.9%	-29%	5.9%
Total		4.1%		100%

Table B.36 – Adults holding a motorcycle subpopulation share by socio-economic variables (1/3)

		Adults with a motorcycle share	Relative deviation from the mean	Adult share
Age	18 to 25	**3.3%**	**-20%**	7.3%
	26 to 35	**5.9%**	**43%**	16.7%
	36 to 45	**7.2%**	**74%**	13.8%
	46 to 55	**7.8%**	**90%**	15.6%
	56 to 65	**3.0%**	**-27%**	19.2%
	66 to 75	**0.8%**	**-80%**	11.9%
	76 an above	**0.1%**	**-98%**	15.4%
Mobility disabled	Yes	**1.2%**	**-72%**	15.2%
	No	**4.6%**	**13%**	84.2%
	N/A	**6.4%**	**56%**	0.6%
Gender	Man	**7.9%**	**91%**	43.6%
	Woman	**1.2%**	**-70%**	56.4%
Highest level of education	Never attended school	0.0%	-100%	0.3%
	Currently studying	**1.6%**	**-61%**	4.7%
	Primary school	**0.5%**	**-87%**	6.5%
	Secondary school	**2.4%**	**-43%**	7.8%
	High school	**5.9%**	**42%**	18.4%
	High school degree	**6.7%**	**62%**	10.6%
	Apprenticeship and other higher education	**6.5%**	**57%**	0.5%
	Higher education	**4.1%**	**-1%**	13.5%
	Bachelor degree and over	**3.9%**	**-5%**	37.3%
	N/A	0.0%	-100%	0.4%
Occupation	Worker	**7.0%**	**70%**	51.3%
	+Full-time job	***7.1%***	***72%***	*47.4%*
	+Part-time job	***6.2%***	***52%***	*3.9%*
	Retired	**0.7%**	**-84%**	33.7%
	Homemaker	**0.0%**	**-100%**	1.4%
	Unemployed	**2.7%**	**-35%**	6.2%
	Student	**1.6%**	**-60%**	4.6%
	Inactive and N/A	**2.0%**	**-52%**	2.9%
Socio-professional category	No professional activity	**1.6%**	**-60%**	4.5%
	Farmer	0.0%	-100%	0.1%
	Blue-collar worker	**4.6%**	**12%**	13.5%
	Worker	**10.1%**	**145%**	6.6%
	Intermediate profession	**6.1%**	**49%**	17.0%
	Craftsman, Retailer and Business leader	**7.9%**	**92%**	2.0%
	Executive and Intellectual profession	**6.9%**	**68%**	18.3%
	Retired	**0.7%**	**-84%**	33.6%
	N/A	**1.4%**	**-67%**	4.3%
Total		**4.1%**		100%

Table B.37 – Adults holding a motorcycle subpopulation share by socio-economic variables (2/3)

		Adults with a motorcycle share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	**1.9%**	**-53%**	33.5%
	Unkown and N/A	**5.2%**	**27%**	66.5%
Number of daily trips made	Less than 2	**3.3%**	**-19%**	27.3%
	3	**5.2%**	**26%**	12.6%
	4	**3.9%**	**-4%**	21.4%
	5	**4.6%**	**11%**	11.6%
	6	**2.9%**	**-30%**	10.0%
	7 and above	**6.8%**	**65%**	11.6%
	N/A	**1.9%**	**-55%**	5.4%
Total		**4.1%**		100%

Table B.38 – Adults holding a motorcycle subpopulation share by socio-economic variables (3/3)

For workers and students		Adults with a motorcycle share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	**6.0%**	**-8%**	31.5%
	In-agglomeration - Dense communes	**5.8%**	**-11%**	34.5%
	In-agglomeration - Predominantly urbanized communes	**9.3%**	**42%**	10.9%
	In-agglomeration - Other communes	**5.6%**	**-15%**	5.5%
	Out-of-agglomeration - Main communes	**4.1%**	**-38%**	1.4%
	Out-of-agglomeration - Other communes	**3.4%**	**-49%**	0.6%
	Rural communes	**4.4%**	**-33%**	1.0%
	N/A	**8.3%**	**27%**	14.4%
Unicity of workplace location	Yes, out of home	**6.1%**	**-7%**	81.2%
	Yes, home	**8.1%**	**23%**	2.9%
	No	**8.5%**	**30%**	15.8%
Car parking available at work/study	Yes	**7.1%**	**9%**	51.2%
	No	**4.5%**	**-32%**	29.9%
	N/A	**8.3%**	**27%**	19.0%
Bike parking available at work/study	Yes	**7.3%**	**11%**	50.6%
	No	**4.2%**	**-36%**	30.4%
	N/A	**8.3%**	**27%**	19.0%
Total		**6.6%**		100%

Table B.39 – Worker or student adults holding a motorcycle subpopulation share by socio-economic variables

		Adults with a bicycle share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	**18.5%**	**-30%**	32.6%
	In-agglomeration - Dense communes	**25.4%**	**-3%**	36.2%
	In-agglomeration - Predominantly urbanized communes	**33.8%**	**29%**	19.3%
	In-agglomeration - Other communes	**36.5%**	**39%**	4.8%
	Out-of-agglomeration - Main communes	**36.8%**	**40%**	3.6%
	Out-of-agglomeration - Other communes	**43.7%**	**67%**	1.7%
	Rural communes	**36.9%**	**41%**	1.8%
Housing type	Other	11.0%	-58%	0.4%
	Collective housing	**24.0%**	**-9%**	86.4%
	Individual Housing	**41.4%**	**58%**	13.3%
Housing surface	Under 30 m²	**18.9%**	**-28%**	19.8%
	31m² to 40m²	**24.6%**	**-6%**	15.7%
	41m² to 50m²	**23.1%**	**-12%**	16.6%
	51m² to 60m²	**27.4%**	**4%**	13.0%
	61m² to 80m²	**31.3%**	**19%**	19.9%
	81m² and over	**33.6%**	**28%**	14.8%
	N/A	16.9%	-35%	0.3%
Household monthly income	Less than €800	**18.2%**	**-30%**	8.5%
	€800 to €1,200	**18.0%**	**-31%**	13.3%
	€1,200 to €1,600	**22.6%**	**-14%**	17.7%
	€1,600 to €2,000	**28.3%**	**8%**	17.6%
	€2,000 to €2,400	**31.3%**	**19%**	13.0%
	€2,400 to €3,000	**31.6%**	**21%**	10.9%
	€3,000 to €3,500	**36.6%**	**40%**	5.5%
	€3,500 to €4,500	**31.7%**	**21%**	4.0%
	Over €4,500	**30.2%**	**15%**	3.6%
	N/A and Refusal	**24.0%**	-9%	5.9%
	Total	**26.2%**		100%

Table B.40 – Adults holding a bike subpopulation share by socio-economic variables (1/3)

		Adults with a bicycle share	Relative deviation from the mean	Adult share
Age	18 to 25	**16.3%**	**-38%**	7.3%
	26 to 35	**27.6%**	**5%**	16.7%
	36 to 45	**36.5%**	**39%**	13.8%
	46 to 55	**35.4%**	**35%**	15.6%
	56 to 65	**28.9%**	**10%**	19.2%
	66 to 75	**23.5%**	**-11%**	11.9%
	76 an above	**9.9%**	**-62%**	15.4%
Mobility disabled	Yes	**12.7%**	**-52%**	15.2%
	No	**28.6%**	**9%**	84.2%
	N/A	**32.8%**	**25%**	0.6%
Gender	Man	**32.3%**	**23%**	43.6%
	Woman	**21.6%**	**-18%**	56.4%
Highest level of education	Never attended school	**0.0%**	**-100%**	0.3%
	Currently studying	**13.9%**	**-47%**	4.7%
	Primary school	**13.8%**	**-48%**	6.5%
	Secondary school	**16.8%**	**-36%**	7.8%
	High school	**25.6%**	**-2%**	18.4%
	High school degree	**26.5%**	**1%**	10.6%
	Apprenticeship and other higher education	**0.2%**	**-99%**	0.5%
	Higher education	**29.0%**	**10%**	13.5%
	Bachelor degree and over	**31.3%**	**19%**	37.3%
	N/A	**46.2%**	**76%**	0.4%
Occupation	Worker	**32.5%**	**24%**	51.3%
	+Full-time job	***32.7%***	***25%***	*47.4%*
	+Part-time job	***30.4%***	***16%***	*3.9%*
	Retired	**20.1%**	**-23%**	33.7%
	Homemaker	**13.6%**	**-48%**	1.4%
	Unemployed	**24.2%**	**-8%**	6.2%
	Student	**13.9%**	**-47%**	4.6%
	Inactive and N/A	**16.4%**	**-38%**	2.9%
Socio-professional category	No professional activity	**14.4%**	**-45%**	4.5%
	Farmer	**12.4%**	**-53%**	0.1%
	Blue-collar worker	**26.2%**	**0%**	13.5%
	Worker	**27.2%**	**4%**	6.6%
	Intermediate profession	**33.7%**	**29%**	17.0%
	Craftsman, Retailer and Business leader	**33.4%**	**27%**	2.0%
	Executive and Intellectual profession	**35.4%**	**35%**	18.3%
	Retired	**20.1%**	**-23%**	33.6%
	N/A	**13.4%**	**-49%**	4.3%
Total		**26.2%**		100%

Table B.41 – Adults holding a bike subpopulation share by socio-economic variables (2/3)

		Adults with a bicycle share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	**22.5%**	**-14%**	33.5%
	Unkown and N/A	**28.1%**	**7%**	66.5%
Number of daily trips made	Less than 2	**22.8%**	**-13%**	27.3%
	3	**27.0%**	**3%**	12.6%
	4	**27.5%**	**5%**	21.4%
	5	**29.1%**	**11%**	11.6%
	6	**31.0%**	**18%**	10.0%
	7 and above	**31.0%**	**18%**	11.6%
	N/A	**11.5%**	**-56%**	5.4%
	Total	**26.2%**		100%

Table B.42 – Adults holding a bike subpopulation share by socio-economic variables (3/3)

For workers and students		Adults with a bicycle share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	**25.4%**	**-18%**	31.5%
	In-agglomeration - Dense communes	**30.6%**	**-1%**	34.5%
	In-agglomeration - Predominantly urbanized communes	**40.8%**	**32%**	10.9%
	In-agglomeration - Other communes	**37.4%**	**21%**	5.5%
	Out-of-agglomeration - Main communes	**42.3%**	**37%**	1.4%
	Out-of-agglomeration - Other communes	**53.4%**	**72%**	0.6%
	Rural communes	**42.7%**	**38%**	1.0%
	N/A	**31.4%**	**1%**	14.4%
Unicity of workplace location	Yes, out of home	**31.0%**	**0%**	81.2%
	Yes, home	**26.9%**	**-13%**	2.9%
	No	**31.8%**	**3%**	15.8%
Car parking available at work/study	Yes	**32.7%**	**6%**	51.2%
	No	**27.8%**	**-10%**	29.9%
	N/A	**31.2%**	**1%**	19.0%
Bike parking available at work/study	Yes	**34.4%**	**11%**	50.6%
	No	**25.2%**	**-19%**	30.4%
	N/A	**31.2%**	**1%**	19.0%
	Total	**31.0%**		100%

Table B.43 – Worker or student adults holding a bike subpopulation share by socio-economic variables

		Adults with a PT pass share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	62.2%	39%	32.6%
	In-agglomeration - Dense communes	45.7%	2%	36.2%
	In-agglomeration - Predominantly urbanized communes	29.6%	-34%	19.3%
	In-agglomeration - Other communes	27.2%	-39%	4.8%
	Out-of-agglomeration - Main communes	22.4%	-50%	3.6%
	Out-of-agglomeration - Other communes	8.8%	-80%	1.7%
	Rural communes	5.5%	-88%	1.8%
Housing type	Other	32.2%	-28%	0.4%
	Collective housing	48.9%	9%	86.4%
	Individual Housing	19.3%	-57%	13.3%
Housing surface	Under 30 m²	63.7%	42%	19.8%
	31m² to 40m²	57.3%	28%	15.7%
	41m² to 50m²	46.8%	4%	16.6%
	51m² to 60m²	42.0%	-7%	13.0%
	61m² to 80m²	35.2%	-21%	19.9%
	81m² and over	20.0%	-55%	14.8%
	N/A	45.5%	1%	0.3%
Household monthly income	Less than €800	62.4%	39%	8.5%
	€800 to €1,200	45.5%	1%	13.3%
	€1,200 to €1,600	46.9%	5%	17.7%
	€1,600 to €2,000	45.5%	1%	17.6%
	€2,000 to €2,400	45.0%	0%	13.0%
	€2,400 to €3,000	41.9%	-7%	10.9%
	€3,000 to €3,500	35.3%	-21%	5.5%
	€3,500 to €4,500	39.0%	-13%	4.0%
	Over €4,500	33.7%	-25%	3.6%
	N/A and Refusal	35.2%	-22%	5.9%
	Total	44.9%		100%

Table B.44 – Adults holding a PT pass subpopulation share by socio-economic variables (1/3)

		Adults with a PT pass share	Relative deviation from the mean	Adult share
Age	18 to 25	**69.3%**	**54%**	7.3%
	26 to 35	**58.5%**	**30%**	16.7%
	36 to 45	**51.1%**	**14%**	13.8%
	46 to 55	**48.0%**	**7%**	15.6%
	56 to 65	**35.0%**	**-22%**	19.2%
	66 to 75	**33.2%**	**-26%**	11.9%
	76 an above	**31.1%**	**-31%**	15.4%
Mobility disabled	Yes	**38.1%**	**-15%**	15.2%
	No	**46.1%**	**3%**	84.2%
	N/A	**49.4%**	**10%**	0.6%
Gender	Man	**45.3%**	**1%**	43.6%
	Woman	**44.6%**	**-1%**	56.4%
Highest level of education	Never attended school	62.4%	39%	0.3%
	Currently studying	**79.3%**	**77%**	4.7%
	Primary school	**33.0%**	**-26%**	6.5%
	Secondary school	**41.6%**	**-7%**	7.8%
	High school	**35.1%**	**-22%**	18.4%
	High school degree	**41.7%**	**-7%**	10.6%
	Apprenticeship and other higher education	**42.2%**	**-6%**	0.5%
	Higher education	**45.2%**	**1%**	13.5%
	Bachelor degree and over	**49.1%**	**9%**	37.3%
	N/A	19.8%	-56%	0.4%
Occupation	Worker	**52.3%**	**17%**	51.3%
	+Full-time job	***52.6%***	***17%***	*47.4%*
	+Part-time job	***49.0%***	***9%***	*3.9%*
	Retired	**30.3%**	**-33%**	33.7%
	Homemaker	**22.0%**	**-51%**	1.4%
	Unemployed	**43.1%**	**-4%**	6.2%
	Student	**80.3%**	**79%**	4.6%
	Inactive and N/A	**41.5%**	**-8%**	2.9%
Socio-professional category	No professional activity	**79.8%**	**78%**	4.5%
	Farmer	87.6%	95%	0.1%
	Blue-collar worker	**54.7%**	**22%**	13.5%
	Worker	**45.2%**	**1%**	6.6%
	Intermediate profession	**52.1%**	**16%**	17.0%
	Craftsman, Retailer and Business leader	**24.6%**	**-45%**	2.0%
	Executive and Intellectual profession	**53.5%**	**19%**	18.3%
	Retired	**30.2%**	**-33%**	33.6%
	N/A	**34.2%**	**-24%**	4.3%
Total		**44.9%**		100%

Table B.45 – Adults holding a PT pass subpopulation share by socio-economic variables (2/3)

		Adults with a PT pass share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	**100.0%**	**123%**	33.5%
	Unkown and N/A	**17.1%**	**-62%**	66.5%
Number of daily trips made	Less than 2	**47.4%**	**6%**	27.3%
	3	**44.9%**	**0%**	12.6%
	4	**46.4%**	**3%**	21.4%
	5	**46.3%**	**3%**	11.6%
	6	**44.8%**	**0%**	10.0%
	7 and above	**43.5%**	**-3%**	11.6%
	N/A	**26.2%**	**-42%**	5.4%
Total		**44.9%**		100%

Table B.46 – Adults holding a PT pass subpopulation share by socio-economic variables (3/3)

For workers and students		Adults with a PT pass share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	**73.9%**	**35%**	31.5%
	In-agglomeration - Dense communes	**55.7%**	**2%**	34.5%
	In-agglomeration - Predominantly urbanized communes	**32.8%**	**-40%**	10.9%
	In-agglomeration - Other communes	**19.7%**	**-64%**	5.5%
	Out-of-agglomeration - Main communes	**8.6%**	**-84%**	1.4%
	Out-of-agglomeration - Other communes	**0.0%**	**-100%**	0.6%
	Rural communes	**16.3%**	**-70%**	1.0%
	N/A	**49.5%**	**-9%**	14.4%
Unicity of workplace location	Yes, out of home	**56.7%**	**4%**	81.2%
	Yes, home	**28.5%**	**-48%**	2.9%
	No	**48.5%**	**-11%**	15.8%
Car parking available at work/study	Yes	**47.9%**	**-12%**	51.2%
	No	**72.0%**	**32%**	29.9%
	N/A	**45.5%**	**-17%**	19.0%
Bike parking available at work/study	Yes	**51.3%**	**-6%**	50.6%
	No	**65.9%**	**21%**	30.4%
	N/A	**45.5%**	**-17%**	19.0%
Total		**54.6%**		100%

Table B.47 – Worker or student adults holding a PT pass subpopulation share by socio-economic variables

		Adults with a bikesharing subscription share	Relative deviation from the mean	Adult share
IAU commune type	Agglomeration center communes	**8.7%**	**133%**	32.6%
	In-agglomeration - Dense communes	**2.1%**	**-43%**	36.2%
	In-agglomeration - Predominantly urbanized communes	**0.4%**	**-89%**	19.3%
	In-agglomeration - Other communes	**0.8%**	**-79%**	4.8%
	Out-of-agglomeration - Main communes	**0.0%**	**-100%**	3.6%
	Out-of-agglomeration - Other communes	**0.0%**	**-100%**	1.7%
	Rural communes	**0.4%**	**-89%**	1.8%
Housing type	Other	0.0%	-100%	0.4%
	Collective housing	**4.3%**	**14%**	86.4%
	Individual Housing	**0.3%**	**-91%**	13.3%
Housing surface	Under 30 m²	**5.7%**	**53%**	19.8%
	31m² to 40m²	**4.7%**	**25%**	15.7%
	41m² to 50m²	**4.7%**	**25%**	16.6%
	51m² to 60m²	**2.9%**	**-22%**	13.0%
	61m² to 80m²	**2.8%**	**-24%**	19.9%
	81m² and over	**1.0%**	**-73%**	14.8%
	N/A	0.0%	-100%	0.3%
Household monthly income	Less than €800	**2.1%**	**-44%**	8.5%
	€800 to €1,200	**1.1%**	**-69%**	13.3%
	€1,200 to €1,600	**2.1%**	**-45%**	17.7%
	€1,600 to €2,000	**3.7%**	**-1%**	17.6%
	€2,000 to €2,400	**4.4%**	**17%**	13.0%
	€2,400 to €3,000	**6.2%**	**65%**	10.9%
	€3,000 to €3,500	**3.2%**	**-14%**	5.5%
	€3,500 to €4,500	**7.7%**	**106%**	4.0%
	Over €4,500	**11.7%**	**212%**	3.6%
	N/A and Refusal	**4.1%**	**10%**	5.9%
	Total	3.7%		100%

Table B.48 – Adults holding a bike sharing subscription subpopulation share by socio-economic variables (1/3)

		Adults with a bikesharing subscription share	Relative deviation from the mean	Adult share
Age	18 to 25	3.6%	-5%	7.3%
	26 to 35	7.9%	112%	16.7%
	36 to 45	4.8%	28%	13.8%
	46 to 55	5.4%	46%	15.6%
	56 to 65	2.6%	-30%	19.2%
	66 to 75	0.7%	-81%	11.9%
	76 an above	0.4%	-90%	15.4%
Mobility disabled	Yes	1.0%	-73%	15.2%
	No	4.2%	13%	84.2%
	N/A	2.9%	-23%	0.6%
Gender	Man	5.0%	33%	43.6%
	Woman	2.8%	-26%	56.4%
Highest level of education	Never attended school	0.0%	-100%	0.3%
	Currently studying	4.8%	29%	4.7%
	Primary school	0.4%	-89%	6.5%
	Secondary school	0.3%	-92%	7.8%
	High school	0.8%	-77%	18.4%
	High school degree	1.8%	-53%	10.6%
	Apprenticeship and other higher education	0.0%	-100%	0.5%
	Higher education	2.6%	-31%	13.5%
	Bachelor degree and over	7.4%	98%	37.3%
	N/A	0.0%	-100%	0.4%
Occupation	Worker	6.0%	62%	51.3%
	+Full-time job	*6.3%*	*69%*	*47.4%*
	+Part-time job	*2.9%*	*-21%*	*3.9%*
	Retired	0.7%	-82%	33.7%
	Homemaker	0.0%	-100%	1.4%
	Unemployed	3.4%	-9%	6.2%
	Student	4.2%	13%	4.6%
	Inactive and N/A	0.3%	-93%	2.9%
Socio-professional category	No professional activity	4.2%	13%	4.5%
	Farmer	0.0%	-100%	0.1%
	Blue-collar worker	3.1%	-17%	13.5%
	Worker	0.9%	-77%	6.6%
	Intermediate profession	4.9%	30%	17.0%
	Craftsman, Retailer and Business leader	2.6%	-30%	2.0%
	Executive and Intellectual profession	10.6%	185%	18.3%
	Retired	0.7%	-82%	33.6%
	N/A	0.2%	-95%	4.3%
Total		3.7%		100%

Table B.49 – Adults holding a bike sharing subscription subpopulation share by socio-economic variables (2/3)

		Adults with a bikesharing subscription share	Relative deviation from the mean	Adult share
PT pass deduction	Aware of it	6.8%	83%	33.5%
	Unkown and N/A	2.2%	-42%	66.5%
Number of daily trips made	Less than 2	3.0%	-20%	27.3%
	3	3.4%	-9%	12.6%
	4	3.9%	5%	21.4%
	5	4.7%	26%	11.6%
	6	5.2%	39%	10.0%
	7 and above	5.0%	34%	11.6%
	N/A	0.0%	-100%	5.4%
Total		3.7%		100%

Table B.50 – Adults holding a bike sharing subscription subpopulation share by socio-economic variables (3/3)

For workers and students		Adults with a bikesharing subscription share	Relative deviation from the mean	Adult share
Workplace location IAU commune type	Agglomeration center communes	9.7%	65%	31.5%
	In-agglomeration - Dense communes	4.5%	-24%	34.5%
	In-agglomeration - Predominantly urbanized communes	3.3%	-44%	10.9%
	In-agglomeration - Other communes	2.4%	-59%	5.5%
	Out-of-agglomeration - Main communes	0.0%	-100%	1.4%
	Out-of-agglomeration - Other communes	0.0%	-100%	0.6%
	Rural communes	0.0%	-100%	1.0%
	N/A	5.4%	-8%	14.4%
Unicity of workplace location	Yes, out of home	6.1%	3%	81.2%
	Yes, home	3.2%	-46%	2.9%
	No	5.4%	-9%	15.8%
Car parking available at work/study	Yes	4.9%	-16%	51.2%
	No	8.1%	38%	29.9%
	N/A	5.0%	-16%	19.0%
Bike parking available at work/study	Yes	5.7%	-3%	50.6%
	No	6.8%	15%	30.4%
	N/A	5.0%	-16%	19.0%
Total		5.9%		100%

Table B.51 – Worker or student adults holding a bike sharing subscription subpopulation share by socio-economic variables

B.3 Multiple holdings data for the subpopulation

		Number of driving licenses		Number of available cars		Number of held parking space		Number of motorcycles		Number of bikes		Number of PT passes		Number of bike sharing subscriptions	
		0	1+	0	1+	0	1+	0	1+	0	1+	0	1+	0	1+
Number of driving licenses	0	18.3%		18.1%	0.2%	18.2%	0.2%	18.0%	0.3%	15.5%	2.8%	6.4%	12.0%	18.0%	0.3%
	1+		81.7%	32.2%	49.5%	49.4%	32.2%	77.9%	3.8%	58.2%	23.4%	48.8%	32.9%	78.2%	3.4%
Number of available cars	0	18.1%	32.2%	50.3%		50.3%	0.0%	48.8%	1.5%	41.1%	9.2%	18.2%	32.1%	47.6%	2.7%
	1+	0.2%	49.5%		49.7%	17.3%	32.4%	47.1%	2.6%	32.6%	17.1%	36.9%	12.8%	48.6%	1.1%
Number of held parking space	0	18.2%	49.4%	50.3%	17.3%	67.6%		65.3%	2.4%	52.9%	14.8%	30.6%	37.0%	64.4%	3.2%
	1+	0.2%	32.2%	0.0%	32.4%		32.4%	30.6%	1.8%	20.9%	11.5%	24.5%	7.9%	31.9%	0.5%
Number of motorcycles	0	18.0%	77.9%	48.8%	47.1%	65.3%	30.6%	95.9%		71.7%	24.2%	51.8%	44.1%	92.4%	3.5%
	1+	0.3%	3.8%	1.5%	2.6%	2.4%	1.8%		4.1%	2.1%	2.0%	3.3%	0.8%	3.9%	0.3%
Number of bikes	0	15.5%	58.2%	41.1%	32.6%	52.9%	20.9%	71.7%	2.1%	73.8%		38.5%	35.3%	71.1%	2.7%
	1+	2.8%	23.4%	9.2%	17.1%	14.8%	11.5%	24.2%	2.0%		26.2%	16.7%	9.6%	25.2%	1.0%
Number of PT passes	0	6.4%	48.8%	18.2%	36.9%	30.6%	24.5%	51.8%	3.3%	38.5%	16.7%	55.1%		53.8%	1.3%
	1+	12.0%	32.9%	32.1%	12.8%	37.0%	7.9%	44.1%	0.8%	35.3%	9.6%		44.9%	42.4%	2.4%
Number of bike sharing subscriptions	0	18.0%	78.2%	47.6%	48.6%	64.4%	31.9%	92.4%	3.9%	71.1%	25.2%	53.8%	42.4%	96.3%	
	1+	0.3%	3.4%	2.7%	1.1%	3.2%	0.5%	3.5%	0.3%	2.7%	1.0%	1.3%	2.4%		3.7%

Table B.52 – Mobility tools co-holding individual rates for the subpopulation

		Number of driving licenses		Number of available cars		Number of held parking space		Number of motorcycles		Number of bikes		Number of PT passes		Number of bike sharing subscriptions		
		0	1+	0	1+	0	1+	0	1+	0	1+	0	1+	0	1+	Share
Number of driving licenses	0	100.0%		98.9%	1.1%	99.2%	0.8%	98.1%	1.9%	84.6%	15.4%	34.7%	65.3%	98.2%	1.8%	18.3%
	1+		100.0%	39.4%	60.6%	60.5%	39.5%	95.4%	4.6%	71.3%	28.7%	59.7%	40.3%	95.8%	4.2%	81.7%
Number of available cars	0	36.0%	64.0%	100.0%		100.0%	0.0%	96.9%	3.1%	81.8%	18.2%	36.2%	63.8%	94.7%	5.3%	50.3%
	1+	0.4%	99.6%		100.0%	34.8%	65.2%	94.8%	5.2%	65.6%	34.4%	74.3%	25.7%	97.9%	2.1%	49.7%
Number of held parking space	0	26.9%	73.1%	74.4%	25.6%	100.0%		96.5%	3.5%	78.2%	21.8%	45.3%	54.7%	95.2%	4.8%	67.6%
	1+	0.5%	99.5%	0.0%	100.0%		100.0%	94.5%	5.5%	64.5%	35.5%	75.7%	24.3%	98.4%	1.6%	32.4%
Number of motorcycles	0	18.8%	81.2%	50.9%	49.1%	68.1%	31.9%	100.0%		74.7%	25.3%	54.0%	46.0%	96.4%	3.6%	95.9%
	1+	8.4%	91.6%	37.6%	62.4%	57.1%	42.9%		100.0%	50.8%	49.2%	80.8%	19.2%	93.6%	6.4%	4.1%
Number of bikes	0	21.0%	79.0%	55.8%	44.2%	71.7%	28.3%	97.2%	2.8%	100.0%		52.2%	47.8%	96.4%	3.6%	73.8%
	1+	10.8%	89.2%	35.0%	65.0%	56.2%	43.8%	92.3%	7.7%		100.0%	63.5%	36.5%	96.0%	4.0%	26.2%
Number of PT passes	0	11.5%	88.5%	33.1%	66.9%	55.5%	44.5%	94.0%	6.0%	69.8%	30.2%	100.0%		97.6%	2.4%	55.1%
	1+	26.7%	73.3%	71.5%	28.5%	82.5%	17.5%	98.2%	1.8%	78.6%	21.4%		100.0%	94.6%	5.4%	44.9%
Number of bike sharing subscriptions	0	18.7%	81.3%	49.5%	50.5%	66.9%	33.1%	96.0%	4.0%	73.8%	26.2%	55.9%	44.1%	100.0%		96.3%
	1+	8.7%	91.3%	71.7%	28.3%	86.5%	13.5%	93.0%	7.0%	71.9%	28.1%	35.1%	64.9%		100.0%	3.7%

Table B.53 – Mobility tools co-holding relative individual shares for the subpopulation

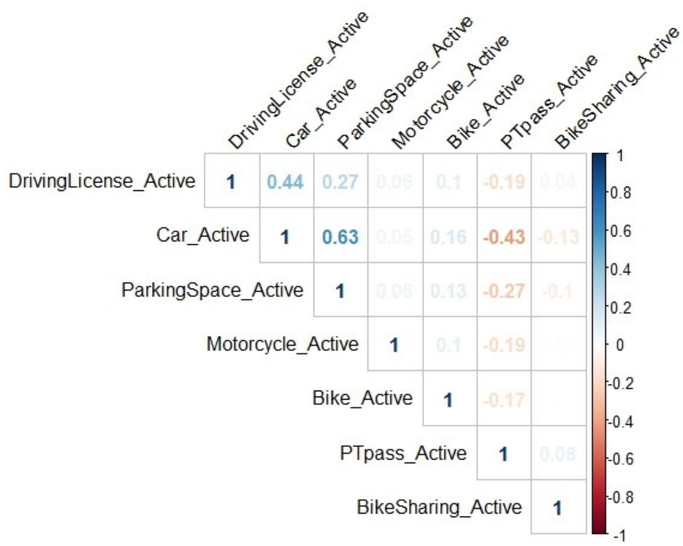

Table B.54 – Weighted correlations matrix of mobility tools holding for the active subpopulation

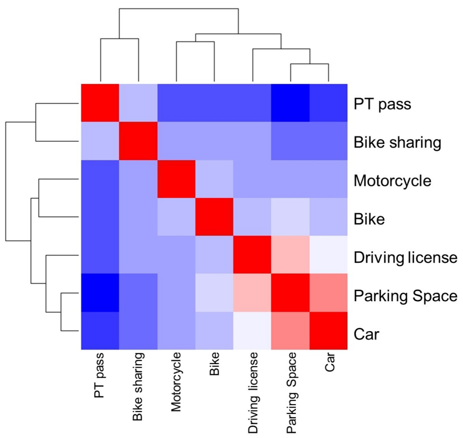

Table B.55 – Weighted correlations distances matrix of mobility tools holding for the active subpopulation

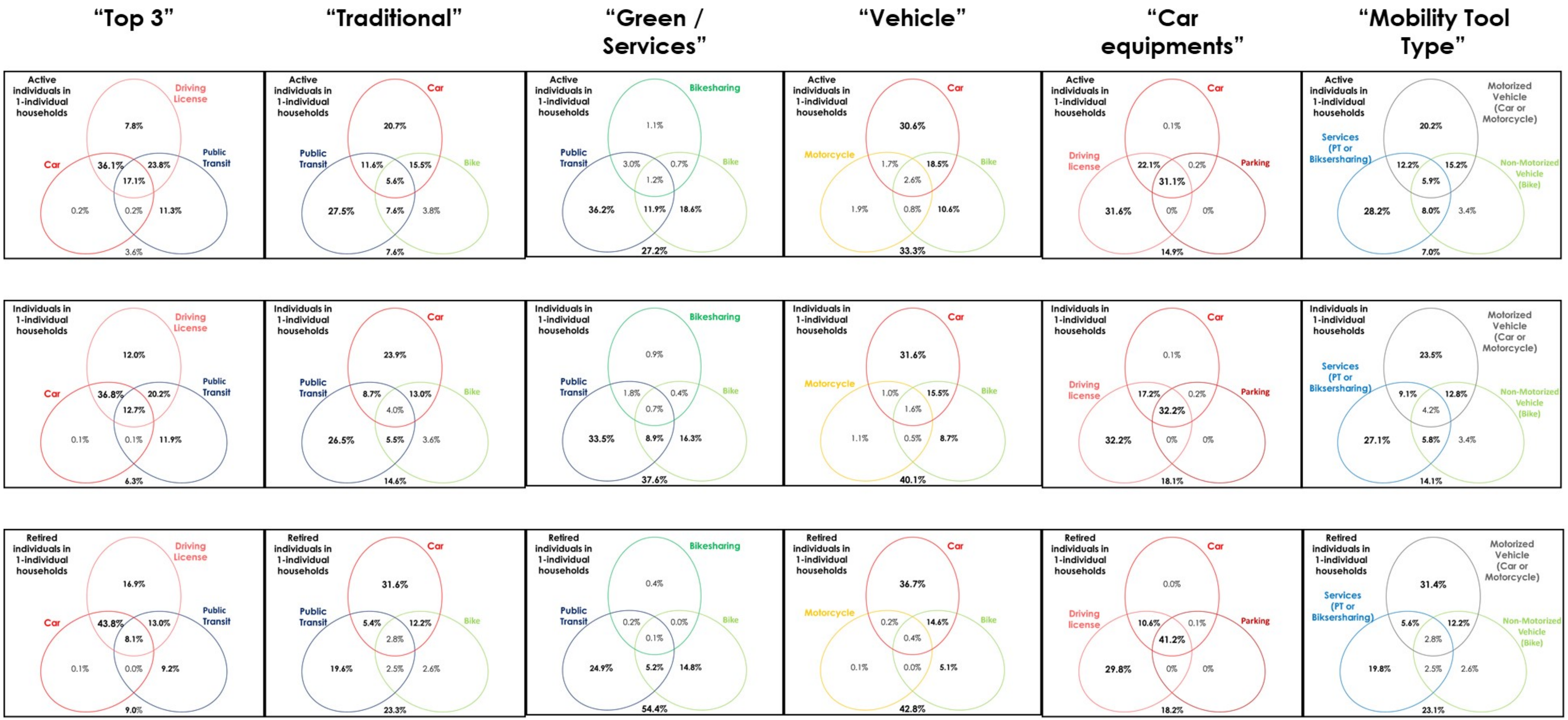

Table B.56 – Three mobility tools holding diagrams for the subpopulation, the active subpopulation and the retired subpopulation

B.4 Portfolio data for the subpopulation

For the subpopulation

Portfolio components							Portfolio size	EGT 2010 share	Paris region share	Paris region cumulative share
Driving license holding	Car holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription				
1	0	0	0	0	1	0	2	12.5%	14.9%	14.9%
1	1	1	0	0	0	0	3	15.7%	14.8%	29.6%
0	0	0	0	0	1	0	1	9.1%	10.0%	39.6%
1	0	0	0	0	0	0	1	7.1%	8.4%	48.0%
1	1	1	0	1	0	0	4	9.8%	7.9%	55.9%
1	1	0	0	0	0	0	2	8.7%	7.9%	63.8%
1	1	1	0	0	1	0	4	5.5%	5.1%	68.9%
0	0	0	0	0	0	0	0	4.4%	4.9%	73.8%
1	1	0	0	1	0	0	3	4.3%	3.6%	77.3%
1	0	0	0	1	1	0	3	2.9%	3.3%	80.6%
1	1	0	0	0	1	0	3	3.3%	3.1%	83.7%
1	1	1	0	1	1	0	5	2.7%	2.3%	86.0%
1	0	0	0	1	0	0	2	2.0%	2.1%	88.2%
0	0	0	0	1	1	0	2	1.4%	1.6%	89.7%
1	1	0	0	1	1	0	4	1.6%	1.4%	91.2%
1	0	0	0	0	1	1	3	1.0%	1.2%	92.4%
0	0	0	0	1	0	0	1	1.2%	1.0%	93.4%
1	1	1	1	1	0	0	5	1.2%	1.0%	94.4%
1	0	0	1	0	0	0	2	0.5%	0.6%	95.0%
1	1	1	1	0	0	0	4	0.6%	0.5%	95.5%
1	0	0	0	0	0	1	2	0.3%	0.5%	96.0%
1	0	0	0	1	1	1	4	0.4%	0.4%	96.4%
1	1	0	1	1	0	0	4	0.4%	0.4%	96.8%
1	1	0	1	0	0	0	3	0.3%	0.3%	97.1%
0	0	0	0	0	1	1	2	0.2%	0.2%	97.3%
0	0	0	1	0	0	0	1	0.2%	0.2%	97.4%
1	0	0	1	1	0	0	3	0.2%	0.2%	97.6%
1	1	0	0	0	0	1	3	0.2%	0.2%	97.8%
1	1	0	0	0	1	1	4	0.2%	0.2%	98.0%
1	1	1	0	0	0	1	4	0.2%	0.2%	98.2%
1	0	0	1	1	1	0	4	0.1%	0.2%	98.3%
1	0	0	1	0	1	0	3	0.1%	0.1%	98.5%
1	1	1	1	0	1	0	5	0.2%	0.1%	98.6%
1	1	1	0	0	1	1	5	0.1%	0.1%	98.7%
1	1	1	0	1	0	1	5	0.1%	0.1%	98.8%
1	0	0	0	1	0	1	3	0.1%	0.1%	98.9%
1	1	0	0	1	1	1	5	0.1%	0.1%	99.0%

Table B.57 – Mobility tools portfolios in the subpopulation (1/3)

0	0	0	1	0	1	0	2	0.1%	0.1%	99.1%
0	1	1	0	0	1	0	3	0.1%	0.1%	99.2%
0	1	1	0	0	0	0	2	0.1%	0.1%	99.2%
1	1	1	1	1	1	0	6	0.1%	0.1%	99.3%
0	0	0	0	1	0	1	2	0.1%	0.1%	99.4%
0	0	0	1	1	0	0	2	0.1%	0.1%	99.4%
1	0	0	1	0	0	1	3	0.0%	0.0%	99.5%
1	0	0	1	1	0	1	4	0.0%	0.0%	99.5%
1	1	0	1	1	1	0	5	0.1%	0.0%	99.6%
1	1	1	0	1	1	1	6	0.1%	0.0%	99.6%
1	1	0	1	0	1	0	4	0.1%	0.0%	99.7%
1	1	1	1	1	1	1	7	0.0%	0.0%	99.7%
1	1	0	1	0	0	1	4	0.0%	0.0%	99.7%
0	1	0	0	0	0	0	1	0.0%	0.0%	99.8%
0	0	0	0	1	1	1	3	0.0%	0.0%	99.8%
1	0	0	1	0	1	1	4	0.0%	0.0%	99.8%
1	1	0	0	1	0	1	4	0.0%	0.0%	99.9%
0	0	0	0	0	0	1	1	0.0%	0.0%	99.9%
1	1	1	1	1	0	1	6	0.0%	0.0%	99.9%
0	1	1	0	1	1	0	4	0.0%	0.0%	99.9%
0	0	0	1	1	1	0	3	0.0%	0.0%	100.0%
1	1	0	1	0	1	1	5	0.0%	0.0%	100.0%
0	1	0	0	1	0	0	2	0.0%	0.0%	100.0%
1	1	0	1	1	0	1	5	0.0%	0.0%	100.0%
0	1	0	0	1	1	0	3	0.0%	0.0%	100.0%
0	1	0	1	0	0	0	2	0.0%	0.0%	100.0%
0	1	0	0	0	1	0	2	0.0%	0.0%	100.0%
0	1	0	0	0	0	1	2	0.0%	0.0%	100.0%
0	0	0	1	0	0	1	2	0.0%	0.0%	100.0%
0	1	0	1	1	0	0	3	0.0%	0.0%	100.0%
0	1	0	1	0	1	0	3	0.0%	0.0%	100.0%
0	1	0	1	0	0	1	3	0.0%	0.0%	100.0%
0	1	0	0	1	0	1	3	0.0%	0.0%	100.0%
0	1	0	0	0	1	1	3	0.0%	0.0%	100.0%
0	0	0	1	1	0	1	3	0.0%	0.0%	100.0%
0	0	0	1	0	1	1	3	0.0%	0.0%	100.0%
0	1	0	1	1	1	0	4	0.0%	0.0%	100.0%
0	1	0	1	1	0	1	4	0.0%	0.0%	100.0%
0	1	0	1	0	1	1	4	0.0%	0.0%	100.0%
0	1	0	0	1	1	1	4	0.0%	0.0%	100.0%
0	0	0	1	1	1	1	4	0.0%	0.0%	100.0%
1	0	0	1	1	1	1	5	0.0%	0.0%	100.0%
0	1	0	1	1	1	1	5	0.0%	0.0%	100.0%
1	1	0	1	1	1	1	6	0.0%	0.0%	100.0%
0	0	1	0	0	0	0	2	0.0%	0.0%	100.0%

Table B.58 – Mobility tools portfolios in the subpopulation (2/3)

1	0	1	0	0	0	0	2	0.0%	0.0%	100.0%
0	0	1	1	0	0	0	2	0.0%	0.0%	100.0%
0	0	1	0	1	0	0	2	0.0%	0.0%	100.0%
0	0	1	0	0	1	0	2	0.0%	0.0%	100.0%
0	0	1	0	0	0	1	2	0.0%	0.0%	100.0%
1	0	1	1	0	0	0	3	0.0%	0.0%	100.0%
1	0	1	0	1	0	0	3	0.0%	0.0%	100.0%
1	0	1	0	0	1	0	3	0.0%	0.0%	100.0%
1	0	1	0	0	0	1	3	0.0%	0.0%	100.0%
0	1	1	1	0	0	0	3	0.0%	0.0%	100.0%
0	1	1	0	1	0	0	3	0.0%	0.0%	100.0%
0	1	1	0	0	0	1	3	0.0%	0.0%	100.0%
0	0	1	1	1	0	0	3	0.0%	0.0%	100.0%
0	0	1	1	0	1	0	3	0.0%	0.0%	100.0%
0	0	1	1	0	0	1	3	0.0%	0.0%	100.0%
0	0	1	0	1	1	0	3	0.0%	0.0%	100.0%
0	0	1	0	1	0	1	3	0.0%	0.0%	100.0%
0	0	1	0	0	1	1	3	0.0%	0.0%	100.0%
1	0	1	1	1	0	0	4	0.0%	0.0%	100.0%
1	0	1	1	0	1	0	4	0.0%	0.0%	100.0%
1	0	1	1	0	0	1	4	0.0%	0.0%	100.0%
1	0	1	0	1	1	0	4	0.0%	0.0%	100.0%
1	0	1	0	1	0	1	4	0.0%	0.0%	100.0%
1	0	1	0	0	1	1	4	0.0%	0.0%	100.0%
0	1	1	1	1	0	0	4	0.0%	0.0%	100.0%
0	1	1	1	0	1	0	4	0.0%	0.0%	100.0%
0	1	1	1	0	0	1	4	0.0%	0.0%	100.0%
0	1	1	0	1	0	1	4	0.0%	0.0%	100.0%
0	1	1	0	0	1	1	4	0.0%	0.0%	100.0%
0	0	1	1	1	1	0	4	0.0%	0.0%	100.0%
0	0	1	1	1	0	1	4	0.0%	0.0%	100.0%
0	0	1	1	0	1	1	4	0.0%	0.0%	100.0%
0	0	1	0	1	1	1	4	0.0%	0.0%	100.0%
1	1	1	1	0	0	1	5	0.0%	0.0%	100.0%
1	0	1	1	1	1	0	5	0.0%	0.0%	100.0%
1	0	1	1	1	0	1	5	0.0%	0.0%	100.0%
1	0	1	1	0	1	1	5	0.0%	0.0%	100.0%
1	0	1	0	1	1	1	5	0.0%	0.0%	100.0%
0	1	1	1	1	1	0	5	0.0%	0.0%	100.0%
0	1	1	1	1	0	1	5	0.0%	0.0%	100.0%
0	1	1	1	0	1	1	5	0.0%	0.0%	100.0%
0	1	1	0	1	1	1	5	0.0%	0.0%	100.0%
0	0	1	1	1	1	1	5	0.0%	0.0%	100.0%
1	1	1	1	0	1	1	6	0.0%	0.0%	100.0%
1	0	1	1	1	1	1	6	0.0%	0.0%	100.0%
0	1	1	1	1	1	1	6	0.0%	0.0%	100.0%

Table B.59 – Mobility tools portfolios in the subpopulation (3/3)

For the active subpopulation

Portfolio components							Portfolio size	EGT 2010 share	Paris region share	Paris region cumulative share
Driving license holding	Car holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription				
1	0	0	0	0	1	0	2	13.6%	16.0%	16.0%
1	1	1	0	0	0	0	3	11.4%	10.3%	26.3%
0	0	0	0	0	1	0	1	8.3%	8.8%	35.1%
1	1	0	0	0	0	0	2	9.2%	8.4%	43.5%
1	1	1	0	1	0	0	4	9.0%	7.8%	51.3%
1	1	1	0	0	1	0	4	6.5%	6.4%	57.7%
1	1	0	0	1	0	0	3	5.9%	5.1%	62.8%
1	0	0	0	1	1	0	3	3.8%	4.4%	67.2%
1	1	0	0	0	1	0	3	4.3%	4.2%	71.4%
1	0	0	0	0	0	0	1	3.3%	3.5%	74.9%
1	1	1	0	1	1	0	5	3.6%	3.0%	77.9%
0	0	0	0	0	0	0	0	2.2%	2.2%	80.1%
1	1	0	0	1	1	0	4	2.4%	2.1%	82.2%
1	0	0	0	1	0	0	2	1.9%	2.0%	84.2%
1	0	0	0	0	1	1	3	1.4%	2.0%	86.2%
0	0	0	0	1	1	0	2	1.9%	1.9%	88.1%
1	1	1	1	1	0	0	5	1.9%	1.6%	89.7%
1	0	0	1	0	0	0	2	0.9%	1.1%	90.8%
0	0	0	0	1	0	0	1	1.0%	1.0%	91.8%
1	0	0	0	1	1	1	4	0.8%	0.9%	92.7%
1	1	1	1	0	0	0	4	0.9%	0.8%	93.5%
1	1	0	1	1	0	0	4	0.6%	0.7%	94.2%
1	0	0	0	0	0	1	2	0.4%	0.5%	94.7%
1	1	0	1	0	0	0	3	0.5%	0.5%	95.2%
0	0	0	0	0	1	1	2	0.3%	0.4%	95.6%
1	0	0	1	1	0	0	3	0.3%	0.3%	95.9%
1	1	0	0	0	1	1	4	0.3%	0.3%	96.2%
1	0	0	1	1	1	0	4	0.2%	0.3%	96.4%
0	0	0	1	0	0	0	1	0.3%	0.3%	96.7%
1	0	0	1	0	1	0	3	0.2%	0.3%	97.0%
1	1	0	0	0	0	1	3	0.2%	0.2%	97.2%
1	1	1	1	0	1	0	5	0.3%	0.2%	97.5%
1	1	1	0	0	1	1	5	0.2%	0.2%	97.7%
1	0	0	0	1	0	1	3	0.2%	0.2%	97.9%
1	1	1	0	0	0	1	4	0.1%	0.2%	98.1%
1	1	1	0	1	0	1	5	0.1%	0.2%	98.3%
1	1	0	0	1	1	1	5	0.1%	0.2%	98.5%

Table B.60 – Mobility tools portfolios in the active subpopulation (1/3)

0	0	0	0	1	0	1	2	0.1%	0.1%	98.6%
0	1	1	0	0	1	0	3	0.1%	0.1%	98.7%
0	0	0	1	1	0	0	2	0.1%	0.1%	98.8%
1	0	0	1	0	0	1	3	0.1%	0.1%	98.9%
1	0	0	1	1	0	1	4	0.1%	0.1%	99.0%
1	1	0	1	1	1	0	5	0.1%	0.1%	99.1%
1	1	0	1	0	1	0	4	0.1%	0.1%	99.1%
1	1	1	1	1	1	0	6	0.1%	0.1%	99.2%
0	0	0	1	0	1	0	2	0.1%	0.1%	99.3%
1	1	0	1	0	0	1	4	0.0%	0.1%	99.4%
0	1	1	0	0	0	0	2	0.1%	0.1%	99.4%
0	1	0	0	0	0	0	1	0.1%	0.1%	99.5%
0	0	0	0	1	1	1	3	0.1%	0.1%	99.6%
1	0	0	1	0	1	1	4	0.0%	0.1%	99.6%
1	1	0	0	1	0	1	4	0.1%	0.1%	99.7%
1	1	1	0	1	1	1	6	0.1%	0.1%	99.7%
1	1	1	1	1	0	1	6	0.1%	0.1%	99.8%
0	1	1	0	1	1	0	4	0.1%	0.0%	99.8%
0	0	0	1	1	1	0	3	0.0%	0.0%	99.9%
1	1	1	1	1	1	1	7	0.0%	0.0%	99.9%
1	1	0	1	0	1	1	5	0.0%	0.0%	99.9%
0	1	0	0	1	0	0	2	0.0%	0.0%	100.0%
1	1	0	1	1	0	1	5	0.0%	0.0%	100.0%
0	1	0	0	1	1	0	3	0.0%	0.0%	100.0%
0	0	0	0	0	0	1	1	0.0%	0.0%	100.0%
0	1	0	1	0	0	0	2	0.0%	0.0%	100.0%
0	1	0	0	0	1	0	2	0.0%	0.0%	100.0%
0	1	0	0	0	0	1	2	0.0%	0.0%	100.0%
0	0	0	1	0	0	1	2	0.0%	0.0%	100.0%
0	1	0	1	1	0	0	3	0.0%	0.0%	100.0%
0	1	0	1	0	1	0	3	0.0%	0.0%	100.0%
0	1	0	1	0	0	1	3	0.0%	0.0%	100.0%
0	1	0	0	1	0	1	3	0.0%	0.0%	100.0%
0	1	0	0	0	1	1	3	0.0%	0.0%	100.0%
0	0	0	1	1	0	1	3	0.0%	0.0%	100.0%
0	0	0	1	0	1	1	3	0.0%	0.0%	100.0%
0	1	0	1	1	1	0	4	0.0%	0.0%	100.0%
0	1	0	1	1	0	1	4	0.0%	0.0%	100.0%
0	1	0	1	0	1	1	4	0.0%	0.0%	100.0%
0	1	0	0	1	1	1	4	0.0%	0.0%	100.0%
0	0	0	1	1	1	1	4	0.0%	0.0%	100.0%
1	0	0	1	1	1	1	5	0.0%	0.0%	100.0%
0	1	0	1	1	1	1	5	0.0%	0.0%	100.0%
1	1	0	1	1	1	1	6	0.0%	0.0%	100.0%
0	0	1	0	0	0	0	1	0.0%	0.0%	100.0%

Table B.61 – Mobility tools portfolios in the active subpopulation (2/3)

1	0	1	0	0	0	0	2	0.0%	0.0%	100.0%
0	0	1	1	0	0	0	2	0.0%	0.0%	100.0%
0	0	1	0	1	0	0	2	0.0%	0.0%	100.0%
0	0	1	0	0	1	0	2	0.0%	0.0%	100.0%
0	0	1	0	0	0	1	2	0.0%	0.0%	100.0%
1	0	1	1	0	0	0	3	0.0%	0.0%	100.0%
1	0	1	0	1	0	0	3	0.0%	0.0%	100.0%
1	0	1	0	0	1	0	3	0.0%	0.0%	100.0%
1	0	1	0	0	0	1	3	0.0%	0.0%	100.0%
0	1	1	1	0	0	0	3	0.0%	0.0%	100.0%
0	1	1	0	1	0	0	3	0.0%	0.0%	100.0%
0	1	1	0	0	0	1	3	0.0%	0.0%	100.0%
0	0	1	1	1	0	0	3	0.0%	0.0%	100.0%
0	0	1	1	0	1	0	3	0.0%	0.0%	100.0%
0	0	1	1	0	0	1	3	0.0%	0.0%	100.0%
0	0	1	0	1	1	0	3	0.0%	0.0%	100.0%
0	0	1	0	1	0	1	3	0.0%	0.0%	100.0%
0	0	1	0	0	1	1	3	0.0%	0.0%	100.0%
1	0	1	1	1	0	0	4	0.0%	0.0%	100.0%
1	0	1	1	0	1	0	4	0.0%	0.0%	100.0%
1	0	1	1	0	0	1	4	0.0%	0.0%	100.0%
1	0	1	0	1	1	0	4	0.0%	0.0%	100.0%
1	0	1	0	1	0	1	4	0.0%	0.0%	100.0%
1	0	1	0	0	1	1	4	0.0%	0.0%	100.0%
0	1	1	1	1	0	0	4	0.0%	0.0%	100.0%
0	1	1	1	0	1	0	4	0.0%	0.0%	100.0%
0	1	1	1	0	0	1	4	0.0%	0.0%	100.0%
0	1	1	0	1	0	1	4	0.0%	0.0%	100.0%
0	1	1	0	0	1	1	4	0.0%	0.0%	100.0%
0	0	1	1	1	1	0	4	0.0%	0.0%	100.0%
0	0	1	1	1	0	1	4	0.0%	0.0%	100.0%
0	0	1	1	0	1	1	4	0.0%	0.0%	100.0%
0	0	1	0	1	1	1	4	0.0%	0.0%	100.0%
1	1	1	1	0	0	1	5	0.0%	0.0%	100.0%
1	0	1	1	1	1	0	5	0.0%	0.0%	100.0%
1	0	1	1	1	0	1	5	0.0%	0.0%	100.0%
1	0	1	1	0	1	1	5	0.0%	0.0%	100.0%
1	0	1	0	1	1	1	5	0.0%	0.0%	100.0%
0	1	1	1	1	1	0	5	0.0%	0.0%	100.0%
0	1	1	1	1	0	1	5	0.0%	0.0%	100.0%
0	1	1	1	0	1	1	5	0.0%	0.0%	100.0%
0	1	1	0	1	1	1	5	0.0%	0.0%	100.0%
0	0	1	1	1	1	1	5	0.0%	0.0%	100.0%
1	1	1	1	0	1	1	6	0.0%	0.0%	100.0%
1	0	1	1	1	1	1	6	0.0%	0.0%	100.0%
0	1	1	1	1	1	1	6	0.0%	0.0%	100.0%

Table B.62 – Mobility tools portfolios in the active subpopulation (3/3)

For the retired subpopulation

Portfolio components							Portfolio size	EGT 2010 share	Paris region share	Paris region cumulative share
Driving license holding	Car holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription				
1	1	1	0	0	0	0	3	25.4%	24.6%	24.6%
1	0	0	0	0	0	0	1	12.7%	14.8%	39.4%
1	0	0	0	0	1	0	2	9.5%	11.1%	50.4%
1	1	1	0	1	0	0	4	12.7%	9.8%	60.2%
0	0	0	0	0	1	0	1	7.2%	8.5%	68.7%
0	0	0	0	0	0	0	0	7.6%	8.2%	76.9%
1	1	0	0	0	0	0	2	7.3%	6.5%	83.4%
1	1	1	0	0	1	0	4	4.9%	4.2%	87.7%
1	1	0	0	1	0	0	3	2.3%	2.1%	89.8%
1	0	0	0	1	0	0	2	1.9%	2.0%	91.7%
1	1	1	0	1	1	0	5	1.8%	1.9%	93.7%
1	0	0	0	1	1	0	3	1.3%	1.8%	95.5%
1	1	0	0	0	1	0	3	1.4%	1.1%	96.5%
1	1	0	0	1	1	0	4	0.6%	0.7%	97.2%
0	0	0	0	1	1	0	2	0.5%	0.7%	97.9%
0	0	0	0	1	0	0	1	1.0%	0.7%	98.6%
1	1	1	1	0	0	0	4	0.2%	0.2%	98.8%
1	1	1	1	1	0	0	5	0.2%	0.2%	99.0%
1	0	0	0	0	0	1	2	0.1%	0.1%	99.2%
1	1	1	0	0	0	1	4	0.2%	0.1%	99.3%
1	1	0	0	0	0	1	3	0.1%	0.1%	99.4%
1	1	0	0	0	1	1	4	0.1%	0.1%	99.5%
1	1	0	1	1	0	0	4	0.1%	0.1%	99.6%
1	0	0	0	0	1	1	3	0.1%	0.1%	99.6%
1	1	1	1	1	1	0	6	0.1%	0.1%	99.7%
0	0	0	0	0	0	1	1	0.1%	0.1%	99.8%
0	0	0	1	0	0	0	1	0.1%	0.1%	99.8%
1	1	1	0	1	1	1	6	0.1%	0.1%	99.9%
0	1	1	0	0	0	0	2	0.1%	0.1%	99.9%
1	1	1	0	1	0	1	5	0.1%	0.0%	100.0%
0	1	1	0	0	1	0	3	0.1%	0.0%	100.0%
0	0	0	1	1	0	0	2	0.1%	0.0%	100.0%
0	1	0	0	0	0	0	1	0.0%	0.0%	100.0%
1	0	0	1	0	0	0	2	0.0%	0.0%	100.0%
0	1	0	1	0	0	0	2	0.0%	0.0%	100.0%
0	1	0	0	1	0	0	2	0.0%	0.0%	100.0%
0	1	0	0	0	1	0	2	0.0%	0.0%	100.0%

Table B.63 – Mobility tools portfolios in the retired subpopulation (1/3)

0	1	0	0	0	0	1	2	0.0%	0.0%	100.0%
0	0	0	1	0	1	0	2	0.0%	0.0%	100.0%
0	0	0	1	0	0	1	2	0.0%	0.0%	100.0%
0	0	0	0	1	0	1	2	0.0%	0.0%	100.0%
0	0	0	0	0	1	1	2	0.0%	0.0%	100.0%
1	1	0	1	0	0	0	3	0.0%	0.0%	100.0%
1	0	0	1	1	0	0	3	0.0%	0.0%	100.0%
1	0	0	1	0	1	0	3	0.0%	0.0%	100.0%
1	0	0	1	0	0	1	3	0.0%	0.0%	100.0%
1	0	0	0	1	0	1	3	0.0%	0.0%	100.0%
0	1	0	1	1	0	0	3	0.0%	0.0%	100.0%
0	1	0	1	0	1	0	3	0.0%	0.0%	100.0%
0	1	0	1	0	0	1	3	0.0%	0.0%	100.0%
0	1	0	0	1	1	0	3	0.0%	0.0%	100.0%
0	1	0	0	1	0	1	3	0.0%	0.0%	100.0%
0	1	0	0	0	1	1	3	0.0%	0.0%	100.0%
0	0	0	1	1	1	0	3	0.0%	0.0%	100.0%
0	0	0	1	1	0	1	3	0.0%	0.0%	100.0%
0	0	0	1	0	1	1	3	0.0%	0.0%	100.0%
0	0	0	0	1	1	1	3	0.0%	0.0%	100.0%
1	1	0	1	0	1	0	4	0.0%	0.0%	100.0%
1	1	0	1	0	0	1	4	0.0%	0.0%	100.0%
1	1	0	0	1	0	1	4	0.0%	0.0%	100.0%
1	0	0	1	1	1	0	4	0.0%	0.0%	100.0%
1	0	0	1	1	0	1	4	0.0%	0.0%	100.0%
1	0	0	1	0	1	1	4	0.0%	0.0%	100.0%
1	0	0	0	1	1	1	4	0.0%	0.0%	100.0%
0	1	0	1	1	1	0	4	0.0%	0.0%	100.0%
0	1	0	1	1	0	1	4	0.0%	0.0%	100.0%
0	1	0	1	0	1	1	4	0.0%	0.0%	100.0%
0	1	0	0	1	1	1	4	0.0%	0.0%	100.0%
0	0	0	1	1	1	1	4	0.0%	0.0%	100.0%
1	1	0	1	1	1	0	5	0.0%	0.0%	100.0%
1	1	0	1	1	0	1	5	0.0%	0.0%	100.0%
1	1	0	1	0	1	1	5	0.0%	0.0%	100.0%
1	1	0	0	1	1	1	5	0.0%	0.0%	100.0%
1	0	0	1	1	1	1	5	0.0%	0.0%	100.0%
0	1	0	1	1	1	1	5	0.0%	0.0%	100.0%
1	1	0	1	1	1	1	6	0.0%	0.0%	100.0%
0	0	1	0	0	0	0	2	0.0%	0.0%	100.0%
1	0	1	0	0	0	0	2	0.0%	0.0%	100.0%
0	0	1	1	0	0	0	2	0.0%	0.0%	100.0%
0	0	1	0	1	0	0	2	0.0%	0.0%	100.0%
0	0	1	0	0	1	0	2	0.0%	0.0%	100.0%
0	0	1	0	0	0	1	2	0.0%	0.0%	100.0%

Table B.64 – Mobility tools portfolios in the retired subpopulation (2/3)

1	0	1	1	0	0	0	3	0.0%	0.0%	100.0%
1	0	1	0	1	0	0	3	0.0%	0.0%	100.0%
1	0	1	0	0	1	0	3	0.0%	0.0%	100.0%
1	0	1	0	0	0	1	3	0.0%	0.0%	100.0%
0	1	1	1	0	0	0	3	0.0%	0.0%	100.0%
0	1	1	0	1	0	0	3	0.0%	0.0%	100.0%
0	1	1	0	0	0	1	3	0.0%	0.0%	100.0%
0	0	1	1	1	0	0	3	0.0%	0.0%	100.0%
0	0	1	1	0	1	0	3	0.0%	0.0%	100.0%
0	0	1	1	0	0	1	3	0.0%	0.0%	100.0%
0	0	1	0	1	1	0	3	0.0%	0.0%	100.0%
0	0	1	0	1	0	1	3	0.0%	0.0%	100.0%
0	0	1	0	0	1	1	3	0.0%	0.0%	100.0%
1	0	1	1	1	0	0	4	0.0%	0.0%	100.0%
1	0	1	1	0	1	0	4	0.0%	0.0%	100.0%
1	0	1	1	0	0	1	4	0.0%	0.0%	100.0%
1	0	1	0	1	1	0	4	0.0%	0.0%	100.0%
1	0	1	0	1	0	1	4	0.0%	0.0%	100.0%
1	0	1	0	0	1	1	4	0.0%	0.0%	100.0%
0	1	1	1	1	0	0	4	0.0%	0.0%	100.0%
0	1	1	1	0	1	0	4	0.0%	0.0%	100.0%
0	1	1	1	0	0	1	4	0.0%	0.0%	100.0%
0	1	1	0	1	1	0	4	0.0%	0.0%	100.0%
0	1	1	0	1	0	1	4	0.0%	0.0%	100.0%
0	1	1	0	0	1	1	4	0.0%	0.0%	100.0%
0	0	1	1	1	1	0	4	0.0%	0.0%	100.0%
0	0	1	1	1	0	1	4	0.0%	0.0%	100.0%
0	0	1	1	0	1	1	4	0.0%	0.0%	100.0%
0	0	1	0	1	1	1	4	0.0%	0.0%	100.0%
1	1	1	1	0	1	0	5	0.0%	0.0%	100.0%
1	1	1	1	0	0	1	5	0.0%	0.0%	100.0%
1	1	1	0	0	1	1	5	0.0%	0.0%	100.0%
1	0	1	1	1	1	0	5	0.0%	0.0%	100.0%
1	0	1	1	1	0	1	5	0.0%	0.0%	100.0%
1	0	1	1	0	1	1	5	0.0%	0.0%	100.0%
1	0	1	0	1	1	1	5	0.0%	0.0%	100.0%
0	1	1	1	1	1	0	5	0.0%	0.0%	100.0%
0	1	1	1	1	0	1	5	0.0%	0.0%	100.0%
0	1	1	1	0	1	1	5	0.0%	0.0%	100.0%
0	1	1	0	1	1	1	5	0.0%	0.0%	100.0%
0	0	1	1	1	1	1	5	0.0%	0.0%	100.0%
1	1	1	1	1	0	1	6	0.0%	0.0%	100.0%
1	1	1	1	0	1	1	6	0.0%	0.0%	100.0%
1	0	1	1	1	1	1	6	0.0%	0.0%	100.0%
0	1	1	1	1	1	1	6	0.0%	0.0%	100.0%
1	1	1	1	1	1	1	7	0.0%	0.0%	100.0%

Table B.65 – Mobility tools portfolios in the retired subpopulation (3/3)

For the subpopulation holding a driving license

Portfolio components						Portfolio size	EGT 2010 share	Paris region share	DL holders share	DL holders cumulative share
Car holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription					
0	0	0	0	1	0	2	12.5%	14.9%	18.2%	18.2%
1	1	0	0	0	0	3	15.7%	14.8%	18.1%	36.3%
0	0	0	0	0	0	1	7.1%	8.4%	10.3%	46.6%
1	1	0	1	0	0	4	9.8%	7.9%	9.7%	56.3%
1	0	0	0	0	0	2	8.7%	7.9%	9.6%	65.9%
1	1	0	0	1	0	4	5.5%	5.1%	6.2%	72.1%
1	0	0	1	0	0	3	4.3%	3.6%	4.4%	76.5%
0	0	0	1	1	0	3	2.9%	3.3%	4.1%	80.6%
1	0	0	0	1	0	3	3.3%	3.1%	3.8%	84.4%
1	1	0	1	1	0	5	2.7%	2.3%	2.8%	87.2%
0	0	0	1	0	0	2	2.0%	2.1%	2.6%	89.8%
1	0	0	1	1	0	4	1.6%	1.4%	1.7%	91.5%
0	0	0	0	1	1	3	1.0%	1.2%	1.5%	93.0%
1	1	1	1	0	0	5	1.2%	1.0%	1.2%	94.2%
0	0	1	0	0	0	2	0.5%	0.6%	0.7%	94.9%
1	1	1	0	0	0	4	0.6%	0.5%	0.6%	95.6%
0	0	0	0	0	1	2	0.3%	0.5%	0.6%	96.1%
0	0	0	1	1	1	4	0.4%	0.4%	0.5%	96.7%
1	0	1	1	0	0	4	0.4%	0.4%	0.5%	97.1%
1	0	1	0	0	0	3	0.3%	0.3%	0.3%	97.5%
0	0	1	1	0	0	3	0.2%	0.2%	0.2%	97.7%
1	0	0	0	0	1	3	0.2%	0.2%	0.2%	97.9%
1	0	0	0	1	1	4	0.2%	0.2%	0.2%	98.1%
1	1	0	0	0	1	4	0.2%	0.2%	0.2%	98.3%
0	0	1	1	1	0	4	0.1%	0.2%	0.2%	98.5%
0	0	1	0	1	0	3	0.1%	0.1%	0.2%	98.7%
1	1	1	0	1	0	5	0.2%	0.1%	0.2%	98.9%
1	1	0	0	1	1	5	0.1%	0.1%	0.1%	99.0%
1	1	0	1	0	1	5	0.1%	0.1%	0.1%	99.2%
0	0	0	1	0	1	3	0.1%	0.1%	0.1%	99.3%

Table B.66 – Mobility tools portfolios in addition to a driving license in the subpopulation (1/2)

1	0	0	1	1	1	5	0.1%	0.1%	0.1%	99.4%
1	1	1	1	1	0	6	0.1%	0.1%	0.1%	99.5%
0	0	1	0	0	1	3	0.0%	0.0%	0.1%	99.5%
0	0	1	1	0	1	4	0.0%	0.0%	0.1%	99.6%
1	0	1	1	1	0	5	0.1%	0.0%	0.1%	99.6%
1	1	0	1	1	1	6	0.1%	0.0%	0.1%	99.7%
1	0	1	0	1	0	4	0.1%	0.0%	0.1%	99.8%
1	1	1	1	1	1	7	0.0%	0.0%	0.1%	99.8%
1	0	1	0	0	1	4	0.0%	0.0%	0.0%	99.9%
0	0	1	0	1	1	4	0.0%	0.0%	0.0%	99.9%
1	0	0	1	0	1	4	0.0%	0.0%	0.0%	99.9%
1	1	1	1	0	1	6	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	0	2	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
1	1	1	0	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	1	0	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%

Table B.67 – Mobility tools portfolios in addition to a driving license in the subpopulation (2/2)

For the subpopulation holding a car

Portfolio components						Portfolio size	EGT 2010 share	Paris region share	Car holders share	Car holders cumulative share
Driving license holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription					
1	1	0	0	0	0	3	15.7%	14.8%	29.7%	29.7%
1	1	0	1	0	0	4	9.8%	7.9%	15.9%	45.6%
1	0	0	0	0	0	2	8.7%	7.9%	15.8%	61.4%
1	1	0	0	1	0	4	5.5%	5.1%	10.2%	71.7%
1	0	0	1	0	0	3	4.3%	3.6%	7.2%	78.8%
1	0	0	0	1	0	3	3.3%	3.1%	6.2%	85.1%
1	1	0	1	1	0	5	2.7%	2.3%	4.6%	89.7%
1	0	0	1	1	0	4	1.6%	1.4%	2.9%	92.6%
1	1	1	1	0	0	5	1.2%	1.0%	2.0%	94.5%
1	1	1	0	0	0	4	0.6%	0.5%	1.0%	95.6%
1	0	1	1	0	0	4	0.4%	0.4%	0.8%	96.4%
1	0	1	0	0	0	3	0.3%	0.3%	0.5%	96.9%
1	0	0	0	0	1	3	0.2%	0.2%	0.4%	97.2%
1	0	0	0	1	1	4	0.2%	0.2%	0.4%	97.6%
1	1	0	0	0	1	4	0.2%	0.2%	0.3%	97.9%
1	1	1	0	1	0	5	0.2%	0.1%	0.3%	98.2%
1	1	0	0	1	1	5	0.1%	0.1%	0.2%	98.4%
1	1	0	1	0	1	5	0.1%	0.1%	0.2%	98.7%
1	0	0	1	1	1	5	0.1%	0.1%	0.2%	98.8%
0	1	0	0	1	0	3	0.1%	0.1%	0.1%	99.0%
0	1	0	0	0	0	2	0.1%	0.1%	0.1%	99.1%
1	1	1	1	1	0	6	0.1%	0.1%	0.1%	99.2%
1	0	1	1	1	0	5	0.1%	0.0%	0.1%	99.3%
1	1	0	1	1	1	6	0.1%	0.0%	0.1%	99.4%
1	0	1	0	1	0	4	0.1%	0.0%	0.1%	99.5%
1	1	1	1	1	1	7	0.0%	0.0%	0.1%	99.6%
1	0	1	0	0	1	4	0.0%	0.0%	0.1%	99.7%
0	0	0	0	0	0	1	0.0%	0.0%	0.1%	99.7%
1	0	0	1	0	1	4	0.0%	0.0%	0.1%	99.8%
1	1	1	1	0	1	6	0.0%	0.0%	0.1%	99.9%

Table B.68 – Mobility tools portfolios in addition to a car in the subpopulation (1/2)

0	1	0	1	1	0	4	0.0%	0.0%	0.0%	99.9%
1	0	1	0	1	1	5	0.0%	0.0%	0.0%	99.9%
0	0	0	1	0	0	2	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	0	2	0.0%	0.0%	0.0%	100.0%
0	0	0	0	1	0	2	0.0%	0.0%	0.0%	100.0%
0	0	0	0	0	1	2	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	1	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	0	1	1	3	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
1	1	1	0	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	1	0	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%

Table B.69 – Mobility tools portfolios in addition to a car in the subpopulation (2/2)

For the subpopulation holding a parking space

Portfolio components						Portfolio size	EGT 2010 share	Paris region share	Parking space holders share	Parking space holders cumulative share
Driving license holding	Car holding	Motorcycle holding	Bike holding	PT pass holding	Bike sharing subscription					
1	1	0	0	0	0	3	15.7%	14.8%	45.6%	45.6%
1	1	0	1	0	0	4	9.8%	7.9%	24.4%	70.0%
1	1	0	0	1	0	4	5.5%	5.1%	15.7%	85.6%
1	1	0	1	1	0	5	2.7%	2.3%	7.1%	92.7%
1	1	1	1	0	0	5	1.2%	1.0%	3.0%	95.8%
1	1	1	0	0	0	4	0.6%	0.5%	1.6%	97.4%
1	1	0	0	0	1	4	0.2%	0.2%	0.5%	97.8%
1	1	1	0	1	0	5	0.2%	0.1%	0.4%	98.3%
1	1	0	0	1	1	5	0.1%	0.1%	0.4%	98.6%
1	1	0	1	0	1	5	0.1%	0.1%	0.3%	99.0%
0	1	0	0	1	0	3	0.1%	0.1%	0.2%	99.2%
0	1	0	0	0	0	2	0.1%	0.1%	0.2%	99.4%
1	1	1	1	1	0	6	0.1%	0.1%	0.2%	99.6%
1	1	0	1	1	1	6	0.1%	0.0%	0.1%	99.7%
1	1	1	1	1	1	7	0.0%	0.0%	0.1%	99.9%
1	1	1	1	0	1	6	0.0%	0.0%	0.1%	99.9%
0	1	0	1	1	0	4	0.0%	0.0%	0.1%	100.0%
0	0	0	0	0	0	1	0.0%	0.0%	0.0%	100.0%
1	0	0	0	0	0	2	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	0	2	0.0%	0.0%	0.0%	100.0%
0	0	0	1	0	0	2	0.0%	0.0%	0.0%	100.0%
0	0	0	0	1	0	2	0.0%	0.0%	0.0%	100.0%
0	0	0	0	0	1	2	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
1	0	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
1	0	0	0	1	0	3	0.0%	0.0%	0.0%	100.0%
1	0	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%

Table B.70 – Mobility tools portfolios in addition to a parking space in the subpopulation (1/2)

0	0	1	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	0	1	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	0	1	1	3	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
1	0	0	1	1	0	4	0.0%	0.0%	0.0%	100.0%
1	0	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
1	0	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	1	4	0.0%	0.0%	0.0%	100.0%
1	1	1	0	0	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
1	0	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	1	0	1	1	6	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%

Table B.71 – Mobility tools portfolios in addition to a parking space in the subpopulation (2/2)

For the subpopulation holding a motorcycle

Portfolio components						Portfolio size	EGT 2010 share	Paris region share	Motorcycle holders share	Motorcycle holders cumulative share
Driving license holding	Car holding	Parking space holding	Bike holding	PT pass holding	Bike sharing subscription					
1	1	1	1	0	0	5	1.2%	1.0%	23.8%	23.8%
1	0	0	0	0	0	2	0.5%	0.6%	14.1%	38.0%
1	1	1	0	0	0	4	0.6%	0.5%	12.5%	50.5%
1	1	0	1	0	0	4	0.4%	0.4%	9.4%	59.9%
1	1	0	0	0	0	3	0.3%	0.3%	6.2%	66.1%
0	0	0	0	0	0	1	0.2%	0.2%	4.7%	70.8%
1	0	0	1	0	0	3	0.2%	0.2%	4.5%	75.3%
1	0	0	1	1	0	4	0.1%	0.2%	3.8%	79.1%
1	0	0	0	1	0	3	0.1%	0.1%	3.6%	82.7%
1	1	1	0	1	0	5	0.2%	0.1%	3.3%	86.0%
0	0	0	0	1	0	2	0.1%	0.1%	2.0%	88.0%
1	1	1	1	1	0	6	0.1%	0.1%	1.6%	89.6%
0	0	0	1	0	0	2	0.1%	0.1%	1.3%	90.9%
1	0	0	0	0	1	3	0.0%	0.0%	1.2%	92.1%
1	0	0	1	0	1	4	0.0%	0.0%	1.2%	93.2%
1	1	0	1	1	0	5	0.1%	0.0%	1.2%	94.4%
1	1	0	0	1	0	4	0.1%	0.0%	1.1%	95.5%
1	1	1	1	1	1	7	0.0%	0.0%	1.1%	96.6%
1	1	0	0	0	1	4	0.0%	0.0%	0.9%	97.5%
1	0	0	0	1	1	4	0.0%	0.0%	0.8%	98.2%
1	1	1	1	0	1	6	0.0%	0.0%	0.6%	98.8%
0	0	0	1	1	0	3	0.0%	0.0%	0.5%	99.3%
1	1	0	0	1	1	5	0.0%	0.0%	0.4%	99.7%
1	1	0	1	0	1	5	0.0%	0.0%	0.3%	100.0%
0	1	0	0	0	0	2	0.0%	0.0%	0.0%	100.0%
0	0	0	0	0	1	2	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	1	0	1	3	0.0%	0.0%	0.0%	100.0%

Table B.72 – Mobility tools portfolios in addition to a motorcycle in the subpopulation (1/2)

0	0	0	0	1	1	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	1	4	0.0%	0.0%	0.0%	100.0%
1	0	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	0	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	0	2	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	1	3	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	1	4	0.0%	0.0%	0.0%	100.0%
1	1	1	0	0	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	1	0	1	1	6	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%

Table B.73 – Mobility tools portfolios in addition to a motorcycle in the subpopulation (2/2)

For the subpopulation holding a bike

Portfolio components						Portfolio size	EGT 2010 share	Paris region share	Bike holders share	Bike holders cumulative share
Driving license holding	Car holding	Parking space holding	Motorcycle holding	PT pass holding	Bike sharing subscription					
1	1	1	0	0	0	4	9.8%	7.9%	30.1%	30.1%
1	1	0	0	0	0	3	4.3%	3.6%	13.6%	43.7%
1	0	0	0	1	0	3	2.9%	3.3%	12.7%	56.3%
1	1	1	0	1	0	5	2.7%	2.3%	8.7%	65.1%
1	0	0	0	0	0	2	2.0%	2.1%	8.1%	73.2%
0	0	0	0	1	0	2	1.4%	1.6%	6.0%	79.2%
1	1	0	0	1	0	4	1.6%	1.4%	5.4%	84.6%
0	0	0	0	0	0	1	1.2%	1.0%	4.0%	88.6%
1	1	1	1	0	0	5	1.2%	1.0%	3.7%	92.4%
1	0	0	0	1	1	4	0.4%	0.4%	1.7%	94.1%
1	1	0	1	0	0	4	0.4%	0.4%	1.5%	95.5%
1	0	0	1	0	0	3	0.2%	0.2%	0.7%	96.2%
1	0	0	1	1	0	4	0.1%	0.2%	0.6%	96.8%
1	1	1	0	0	1	5	0.1%	0.1%	0.4%	97.2%
1	0	0	0	0	1	3	0.1%	0.1%	0.4%	97.6%
1	1	0	0	1	1	5	0.1%	0.1%	0.3%	98.0%
1	1	1	1	1	0	6	0.1%	0.1%	0.2%	98.2%
0	0	0	0	0	1	2	0.1%	0.1%	0.2%	98.5%
0	0	0	1	0	0	2	0.1%	0.1%	0.2%	98.7%
1	0	0	1	0	1	4	0.0%	0.0%	0.2%	98.9%
1	1	0	1	1	0	5	0.1%	0.0%	0.2%	99.0%
1	1	1	0	1	1	6	0.1%	0.0%	0.2%	99.2%
1	1	1	1	1	1	7	0.0%	0.0%	0.2%	99.4%
0	0	0	0	1	1	3	0.0%	0.0%	0.1%	99.5%
1	1	0	0	0	1	4	0.0%	0.0%	0.1%	99.6%
1	1	1	1	0	1	6	0.0%	0.0%	0.1%	99.7%
0	1	1	0	1	0	4	0.0%	0.0%	0.1%	99.8%
0	0	0	1	1	0	3	0.0%	0.0%	0.1%	99.9%
0	1	0	0	0	0	2	0.0%	0.0%	0.0%	99.9%
1	1	0	1	0	1	5	0.0%	0.0%	0.0%	100.0%

Table B.74 – Mobility tools portfolios in addition to a bike in the subpopulation (1/2)

0	1	0	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	1	0	1	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	1	4	0.0%	0.0%	0.0%	100.0%
1	0	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	0	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	0	2	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	1	3	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	1	4	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%

Table B.75 – Mobility tools portfolios in addition to a bike in the subpopulation (2/2)

For the subpopulation holding a PT pass

Portfolio components						Portfolio size	EGT 2010 share	Paris region share	PT pass holders share	PT pass holders cumulative share
Driving license holding	Car holding	Parking space holding	Motorcycle holding	Bike holding	Bike sharing subscription					
1	0	0	0	0	0	2	12.5%	14.9%	33.2%	33.2%
0	0	0	0	0	0	1	9.1%	10.0%	22.2%	55.4%
1	1	1	0	0	0	4	5.5%	5.1%	11.3%	66.7%
1	0	0	0	1	0	3	2.9%	3.3%	7.4%	74.1%
1	1	0	0	0	0	3	3.3%	3.1%	6.9%	81.0%
1	1	1	0	1	0	5	2.7%	2.3%	5.1%	86.2%
0	0	0	0	1	0	2	1.4%	1.6%	3.5%	89.6%
1	1	0	0	1	0	4	1.6%	1.4%	3.2%	92.8%
1	0	0	0	0	1	3	1.0%	1.2%	2.7%	95.5%
1	0	0	0	1	1	4	0.4%	0.4%	1.0%	96.5%
0	0	0	0	0	1	2	0.2%	0.2%	0.5%	97.0%
1	1	0	0	0	1	4	0.2%	0.2%	0.4%	97.4%
1	0	0	1	1	0	4	0.1%	0.2%	0.3%	97.7%
1	0	0	1	0	0	3	0.1%	0.1%	0.3%	98.1%
1	1	1	1	0	0	5	0.2%	0.1%	0.3%	98.4%
1	1	1	0	0	1	5	0.1%	0.1%	0.3%	98.6%
1	1	0	0	1	1	5	0.1%	0.1%	0.2%	98.8%
0	0	0	1	0	0	2	0.1%	0.1%	0.2%	99.0%
0	1	1	0	0	0	3	0.1%	0.1%	0.1%	99.2%
1	1	1	1	1	0	6	0.1%	0.1%	0.1%	99.3%
1	1	0	1	1	0	5	0.1%	0.0%	0.1%	99.4%
1	1	1	0	1	1	6	0.1%	0.0%	0.1%	99.5%
1	1	0	1	0	0	4	0.1%	0.0%	0.1%	99.6%
1	1	1	1	1	1	7	0.0%	0.0%	0.1%	99.7%
0	0	0	0	1	1	3	0.0%	0.0%	0.1%	99.8%
1	0	0	1	0	1	4	0.0%	0.0%	0.1%	99.9%
0	1	1	0	1	0	4	0.0%	0.0%	0.0%	99.9%
0	0	0	1	1	0	3	0.0%	0.0%	0.0%	100.0%
1	1	0	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	0	3	0.0%	0.0%	0.0%	100.0%

Table B.76 – Mobility tools portfolios in addition to a PT pass in the subpopulation (1/2)

0	1	0	0	0	0	2	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	1	0	1	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	1	4	0.0%	0.0%	0.0%	100.0%
1	0	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	0	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	0	2	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	1	3	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	1	4	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	1	1	0	1	6	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%

Table B.77 – Mobility tools portfolios in addition to a PT pass in the subpopulation (2/2)

For the subpopulation holding a bike sharing subscription

Portfolio components						Portfolio size	EGT 2010 share	Paris region share	Bike sharing subscribers share	Bike sharing subscribers cumulative share
Driving license holding	Car holding	Parking space holding	Motorcycle holding	Bike holding	PT pass holding					
1	0	0	0	0	1	3	1.0%	1.2%	32.6%	32.6%
1	0	0	0	0	0	2	0.3%	0.5%	12.4%	45.0%
1	0	0	0	1	1	4	0.4%	0.4%	11.9%	56.8%
0	0	0	0	0	1	2	0.2%	0.2%	5.5%	62.3%
1	1	0	0	0	0	3	0.2%	0.2%	5.0%	67.3%
1	1	0	0	0	1	4	0.2%	0.2%	4.9%	72.2%
1	1	1	0	0	0	4	0.2%	0.2%	4.2%	76.4%
1	1	1	0	0	1	5	0.1%	0.1%	3.1%	79.5%
1	1	1	0	1	0	5	0.1%	0.1%	2.9%	82.5%
1	0	0	0	1	0	3	0.1%	0.1%	2.8%	85.2%
1	1	0	0	1	1	5	0.1%	0.1%	2.4%	87.7%
0	0	0	0	1	0	2	0.1%	0.1%	1.6%	89.3%
1	0	0	1	0	0	3	0.0%	0.0%	1.3%	90.6%
1	0	0	1	1	0	4	0.0%	0.0%	1.3%	91.9%
1	1	1	0	1	1	6	0.1%	0.0%	1.3%	93.2%
1	1	1	1	1	1	7	0.0%	0.0%	1.2%	94.4%
1	1	0	1	0	0	4	0.0%	0.0%	1.0%	95.3%
0	0	0	0	1	1	3	0.0%	0.0%	0.9%	96.2%
1	0	0	1	0	1	4	0.0%	0.0%	0.8%	97.0%
1	1	0	0	1	0	4	0.0%	0.0%	0.8%	97.8%
0	0	0	0	0	0	1	0.0%	0.0%	0.7%	98.6%
1	1	1	1	1	0	6	0.0%	0.0%	0.7%	99.2%
1	1	0	1	0	1	5	0.0%	0.0%	0.4%	99.7%
1	1	0	1	1	0	5	0.0%	0.0%	0.3%	100.0%
0	1	0	0	0	0	2	0.0%	0.0%	0.0%	100.0%
0	0	0	1	0	0	2	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	1	0	0	0	1	3	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	0	3	0.0%	0.0%	0.0%	100.0%

Table B.78 – Mobility tools portfolios in addition to a bike sharing subscription in the subpopulation (1/2)

0	0	0	1	0	1	3	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	0	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	0	0	1	1	4	0.0%	0.0%	0.0%	100.0%
0	0	0	1	1	1	4	0.0%	0.0%	0.0%	100.0%
1	0	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	0	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	0	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	0	2	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	0	3	0.0%	0.0%	0.0%	100.0%
0	0	1	0	0	1	3	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
1	0	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	0	4	0.0%	0.0%	0.0%	100.0%
0	1	1	0	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	0	4	0.0%	0.0%	0.0%	100.0%
0	0	1	1	0	1	4	0.0%	0.0%	0.0%	100.0%
0	0	1	0	1	1	4	0.0%	0.0%	0.0%	100.0%
1	1	1	1	0	0	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
1	0	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
1	0	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	0	5	0.0%	0.0%	0.0%	100.0%
0	1	1	1	0	1	5	0.0%	0.0%	0.0%	100.0%
0	1	1	0	1	1	5	0.0%	0.0%	0.0%	100.0%
0	0	1	1	1	1	5	0.0%	0.0%	0.0%	100.0%
1	1	1	1	0	1	6	0.0%	0.0%	0.0%	100.0%
1	0	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%
0	1	1	1	1	1	6	0.0%	0.0%	0.0%	100.0%

Table B.79 – Mobility tools portfolios in addition to a bike sharing subscription in the subpopulation (2/2)

Appendix C

Intermodality data

C.1 Individual variables

		Paris region adults share	Paris region intermodal adults share	Active 1-individual household share	Intermodal active 1-individual household share
IAU commune type	Agglomeration center communes	26.2%	18.0%	40.8%	27.3%
	In-agglomeration - Dense communes	30.8%	22.2%	28.7%	23.0%
	In-agglomeration - Predominantly urbanized communes	24.2%	33.1%	19.8%	37.2%
	In-agglomeration - Other communes	7.5%	11.4%	5.0%	4.5%
	Out-of-agglomeration - Main communes	4.4%	6.2%	3.4%	4.8%
	Out-of-agglomeration - Other communes	3.0%	4.0%	1.1%	0.8%
	Rural communes	3.8%	5.1%	1.2%	2.3%
Housing type	Other	0.2%	0.1%	0.2%	0.0%
	Collective housing	69.0%	52.1%	89.3%	75.8%
	Individual Housing	30.8%	47.9%	10.5%	24.2%
Housing surface	Under 50 m²	21.5%	15.6%	61.3%	60.3%
	51m² to 70m²	23.4%	17.4%	23.8%	16.0%
	71m² to 90m²	23.4%	19.2%	8.6%	11.2%
	91m² to 110m²	13.6%	17.5%	3.3%	2.7%
	111m² to 150m²	12.0%	16.3%	2.3%	8.8%
	151m² and over	6.2%	13.9%	0.7%	1.0%
Household monthly income	Less than €1,200	9.1%	3.4%	8.8%	7.9%
	€1,200 to €1,600	9.1%	3.9%	18.2%	9.7%
	€1,600 to €2,000	9.7%	5.7%	21.5%	18.9%
	€2,000 to €2,400	9.2%	8.7%	16.4%	25.0%
	€2,400 to €3,000	11.6%	9.4%	14.0%	10.5%
	€3,000 to €3,500	10.1%	11.3%	6.7%	9.7%
	€3,500 to €4,500	13.2%	19.1%	5.4%	5.8%
	€4,500 to €5,500	8.3%	10.9%	2.3%	3.1%
	Over €5,500	12.4%	22.4%	3.0%	8.7%
	N/A and Refusal	7.2%	5.4%	3.7%	0.8%
Number of individuals per household	1	20.8%	14.7%	100%	100%
	2	31.0%	27.8%		
	3	18.4%	22.0%		
	4 and over	29.7%	35.5%		
	Average	2.8	3.0	1	1
Mobility Disability	Yes	9.2%	5.4%	6.1%	5.9%
	No	89.7%	94.5%	93.6%	94.1%
	N/A	1.1%	0.1%	0.4%	0.0%
	Adult Population share	**100%**	**4.7%**	**8.5%**	**0.4%**
	Observations	25,453	1,333	2,217	111
	Estimated individual number	8,741,189	411,375	742,679	36,781
	Sample penetration rate	0.291%	0.324%	0.299%	0.302%

Table C.1 – Individual variables effects on intermodality for Paris region subpopulations (1/3)

		Paris region adults share	Paris region intermodal adults share	Active 1-individual household share	Intermodal active 1-individual household share
Age	18 to 24	9.6%	10.2%	4.3%	5.6%
	25 to 34	18.9%	22.2%	28.0%	26.7%
	35 to 54	40.5%	48.5%	48.6%	48.2%
	55 to 64	15.1%	13.1%	18.1%	18.3%
	65 to 74	8.4%	4.1%	0.9%	1.2%
	75 and above	7.5%	1.8%	0.1%	0.0%
	Average	46.2	42.1	42.2	41.8
Gender	Man	46.9%	46.1%	53.0%	47.7%
	Woman	53.1%	53.9%	47.0%	52.3%
Highest level of education	Never attended school	0.8%	0.5%	0.4%	0.0%
	Primary school	5.5%	0.9%	1.7%	1.9%
	Secondary school	7.7%	3.8%	4.4%	2.1%
	High school	20.7%	13.3%	15.2%	7.9%
	High school degree	10.9%	10.9%	10.6%	9.7%
	Apprenticeship and other higher education	0.5%	0.6%	0.7%	1.3%
	Higher education	13.4%	16.1%	16.8%	15.9%
	Bachelor degree and over	33.4%	45.9%	49.9%	61.3%
	Currently studying	6.8%	8.1%	0.2%	0.0%
	N/A	0.3%	0.0%	0.1%	0.0%
Occupation	Worker	58.6%	76.3%	100.0%	100.0%
	+Full-time job	*52.5%*	*70.0%*	*94.0%*	*94.7%*
	+Part-time job	*6.1%*	*6.3%*	*6.0%*	*5.3%*
	Retired	19.8%	8.1%		
	Homemaker	5.9%	2.7%		
	Unemployed	6.8%	4.2%		
	Student	6.6%	8.0%		
	Inactive and N/A	2.3%	0.8%		
Socio-professional category	No professional activity	6.5%	7.9%	0.0%	0.0%
	Farmer	0.1%	0.4%	0.0%	0.0%
	Employee	17.4%	16.8%	22.7%	16.6%
	Blue-collar worker	9.8%	6.8%	9.9%	2.7%
	Intermediate profession	17.2%	24.6%	30.1%	33.2%
	Craftsman, Retailer and Business leader	2.8%	2.0%	3.6%	7.8%
	Executive and Intellectual profession	17.7%	29.2%	33.7%	39.7%
	Retired	19.8%	8.1%	0.0%	0.0%
	N/A	8.8%	4.3%	0.0%	0.0%
	Adult Population share	**100%**	**4.7%**	**8.5%**	**0.4%**
	Observations	25,453	1,333	2,217	111
	Estimated individual number	8,741,189	411,375	[illegible]	[illegible]
	Sample penetration rate	0.291%	0.324%		

Table C.2 – Individual variables effects on intermodality for Paris region subpopulations (2/3)

		Paris region adults share	Paris region intermodal adults share	Active 1-individual household share	Intermodal active 1-individual household share
Number of daily trips	0	7.5%			
	1 to 2	27.8%	31.8%	29.8%	35.9%
	3	10.4%	16.2%	14.1%	15.3%
	4	20.2%	21.2%	22.5%	13.8%
	5	10.0%	12.6%	12.9%	19.0%
	6	9.9%	7.9%	10.7%	10.5%
	7 to 8	8.9%	6.9%	7.4%	3.2%
	9 to 10	3.1%	1.9%	1.8%	2.3%
	More than 10	2.2%	1.5%	0.9%	0.0%
	Average	4.0	3.9	4.0	3.7
Number of available cars in the household	0	24.1%	14.7%	46.2%	36.6%
	1	45.9%	39.1%	50.4%	58.2%
	2	24.8%	36.6%	3.0%	5.2%
	3 and above	5.2%	9.7%	0.4%	0.0%
	Average	1.1	1.4	0.6	0.7
PT subscription	Yes	38.1%	72.5%	54.2%	77.7%
	No	61.9%	27.5%	45.8%	22.3%
PT subscription and car available	Yes	22.6%	61.0%	17.7%	45.5%
	No	77.4%	39.0%	82.3%	54.5%
	Adult Population share	**100%**	**4.7%**	**8.5%**	**0.4%**
	Observations	25,453	1,333	2,217	111
	Estimated individual number	8,741,189	411,375	742,679	36,781
	Sample penetration rate	0.291%	0.324%	0.299%	0.302%

Table C.3 – Individual variables effects on intermodality for Paris region subpopulations (3/3)

For active individuals		Paris region active adults share	Paris region intermodal active adults share	Active 1-individual household share	Intermodal active 1-individual household share
Workplace location IAU commune type	Agglomeration center communes	33.1%	51.4%	39.8%	42.1%
	In-agglomeration - Dense communes	25.3%	19.9%	27.3%	24.4%
	In-agglomeration - Predominantly urbanized communes	15.0%	9.1%	11.3%	8.4%
	In-agglomeration - Other communes	6.2%	2.9%	6.0%	4.6%
	Out-of-agglomeration - Main communes	2.7%	1.3%	1.5%	0.0%
	Out-of-agglomeration - Other communes	1.2%	0.7%	0.7%	0.0%
	Rural communes	1.6%	0.6%	0.8%	1.2%
	N/A	14.7%	14.0%	12.6%	19.2%
Company Car	Not available in the household	91.2%	91.7%	95.7%	94.1%
	Available in the household	8.8%	8.3%	4.3%	5.9%
	Active Adult population share	**100%**	**3.8%**	**18.2%**	**0.6%**
	Observations	15,852	1,046	2,217	111
	Estimated individual number	5,121,364	313,799	742,679	36,781
	Sample penetration rate	0.310%	0.333%	0.299%	0.302%

Table C.4 – Socio-Economic Individual variables effects on intermodality for active individuals

C.2 Trip variables

For all of the trips

Commune of origin	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	N/A	
Agglomeration center	0.6%	5.2%	11.5%	10.8%	2.7%	0.0%	**30.8%**
Agglomeration	1.7%	13.2%	20.4%	20.2%	3.5%	0.0%	**59.1%**
Out of Agglomeration	0.2%	1.5%	2.5%	2.4%	0.3%	0.0%	**7.0%**
Rural	0.1%	0.7%	0.8%	0.8%	0.1%	0.0%	**2.6%**
N/A	0.0%	0.0%	0.1%	0.2%	0.0%	0.0%	**0.4%**
	2.7%	**20.6%**	**35.4%**	**34.5%**	**6.7%**	**0.1%**	**100%**

For the study population trips

Commune of origin	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	
Agglomeration center	0.6%	3.1%	5.4%	22.7%	5.2%	**37.0%**
Agglomeration	4.9%	20.3%	7.8%	11.7%	1.6%	**46.2%**
Out of Agglomeration	1.5%	3.8%	1.0%	1.5%	0.0%	**7.8%**
Rural	1.1%	1.9%	0.4%	0.4%	0%	**3.7%**
N/A	0.2%	0.2%	1.7%	2.9%	0.3%	**5.3%**
	8.2%	**29.2%**	**16.3%**	**39.2%**	**7.2%**	**100%**

For the study population trips

Commune of origin	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	
Agglomeration center	1.8%	8.7%	14.7%	15.2%	6.3%	**46.7%**
Agglomeration	3.1%	10.3%	13.1%	17.4%	4.3%	**48.3%**
Out of Agglomeration	0.3%	0.7%	0.9%	1.3%	0.4%	**3.6%**
Rural	0.1%	0.2%	0.3%	0.3%	0.1%	**1.0%**
N/A	0.0%	0.0%	0.1%	0.2%	0.1%	**0.4%**
	5.4%	**20.1%**	**29.1%**	**34.4%**	**11.1%**	**100%**

For the study population intermodal trips

Commune of origin	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	
Agglomeration center	0.8%	6.9%	4.2%	15.2%	9.4%	**36.5%**
Agglomeration	6.9%	19.9%	2.3%	13.2%	4.7%	**47.0%**
Out of Agglomeration	1.4%	3.2%	0.1%	0.7%	0%	**5.4%**
Rural	0.9%	0.5%	0.8%	0.6%	0%	**2.9%**
N/A	1.3%	0%	1.2%	4.8%	0.9%	**8.3%**
	11.4%	**30.6%**	**8.6%**	**34.4%**	**15.0%**	**100%**

Table C.5 – Paris region trips origin commune and departure time bivariate distribution

For all of the trips

Commune of destination	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	N/A	
Agglomeration center	1.0%	6.4%	11.5%	9.7%	2.4%	0.0%	**30.9%**
Agglomeration	1.5%	12.3%	20.4%	21.1%	3.8%	0.0%	**59.2%**
Out of Agglomeration	0.1%	1.4%	2.5%	2.6%	0.4%	0.0%	**7.0%**
Rural	0.1%	0.5%	0.8%	1.1%	0.2%	0.0%	**2.6%**
N/A	0.0%	0.1%	0.1%	0.0%	0.0%	0%	**0.2%**
	2.7%	**20.6%**	**35.4%**	**34.5%**	**6.7%**	**0.1%**	**100%**

For the study population trips

Commune of destination	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	
Agglomeration center	4.3%	19.2%	7.7%	7.0%	1.5%	**39.7%**
Agglomeration	3.0%	7.7%	6.7%	25.2%	5.0%	**47.5%**
Out of Agglomeration	0.3%	0.9%	0.8%	4.5%	0.5%	**7.1%**
Rural	0.1%	0.5%	0.7%	2.4%	0.1%	**3.8%**
N/A	0.5%	0.8%	0.4%	0.1%	0.1%	**1.9%**
	8.2%	**29.2%**	**16.3%**	**39.2%**	**7.2%**	**100%**

For the study population trips

Commune of destination	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	
Agglomeration center	2.2%	9.1%	14.5%	15.2%	5.8%	**46.9%**
Agglomeration	2.9%	10.1%	13.3%	17.3%	4.7%	**48.2%**
Out of Agglomeration	0.2%	0.5%	0.9%	1.5%	0.5%	**3.6%**
Rural	0.1%	0.2%	0.3%	0.4%	0.1%	**1.0%**
N/A	0.1%	0.1%	0.1%	0.1%	0.0%	**0.3%**
	5.4%	**20.1%**	**29.1%**	**34.4%**	**11.1%**	**100%**

For the study population intermodal trips

Commune of destination	Departure time: AM offpeak	AM peak	Noon offpeak	PM peak	PM offpeak	
Agglomeration center	4.0%	19.1%	2.7%	8.0%	3.9%	**37.7%**
Agglomeration	5.1%	6.6%	4.9%	22.1%	10.3%	**49.1%**
Out of Agglomeration	0%	0.7%	0.3%	3.2%	0%	**4.2%**
Rural	0%	0.8%	0.1%	1.1%	0%	**2.0%**
N/A	2.3%	3.4%	0.5%	0%	0.9%	**7.1%**
	11.4%	**30.6%**	**8.6%**	**34.4%**	**15.0%**	**100%**

Table C.6 – Paris region trips destination commune and departure time bivariate distribution

		All of the Paris region trips share	Paris region intermodal trips share	Study population trips share	Study population intermodal trips share
Trip purpose	Home-Work	17.4%	51.7%	44.5%	69.7%
	Home-Study	11.0%	9.3%	0.1%	0%
	Home-Purchase	13.5%	2.8%	9.3%	1.2%
	Home-Personnal business	6.1%	3.8%	2.5%	0.5%
	Home-Accompaniment	12.3%	0.7%	1.0%	1.5%
	Home-Leisure	15.9%	13.6%	11.0%	4.2%
	Home-Other	0.2%	0.8%	0.2%	1.9%
	Secondary-Work	11.3%	12.9%	26.8%	17.8%
	Secondary-Other	12.3%	4.3%	4.7%	3.2%
	N/A	0.0%	0.1%	0%	0%
Trip length	Under 500m	29.8%	0.0%	22%	0%
	500m to 1000m	15.3%	0.1%	9.7%	0%
	1km to 1.5km	7.7%	0.5%	6.7%	0%
	1.5km to 2km	5.2%	0.3%	4.9%	0%
	2km to 3km	7.2%	1.0%	7.9%	0.4%
	3km to 5km	9.2%	3.4%	11.7%	3.2%
	5km to 10km	11.7%	12.9%	17.4%	16.9%
	10km to 20km	8.7%	34.9%	12.6%	34.0%
	20km and over	4.6%	39.7%	6.1%	30.3%
	N/A	0.6%	7.2%	0.8%	15.3%
	Average (km)	4.4	19.9	5.8	17.7
Declared trip duration	0 to 5min	22.2%	0.0%	18%	0%
	6 to 10min	19.7%	0.3%	13.6%	0%
	11 to 15min	15.8%	0.3%	12.2%	0%
	16 to 20min	7.6%	0.9%	7.1%	0%
	21 to 25min	3.2%	1.3%	3.4%	0.4%
	26 to 30min	10.2%	2.8%	12.3%	3.8%
	31 to 45min	8.3%	12.5%	13.6%	12.2%
	46 to 60min	6.1%	22.3%	9.4%	23.7%
	61 to 90min	4.6%	34.5%	7.1%	25.3%
	Over 90min	1.8%	17.9%	2.6%	19.3%
	N/A	0.7%	7.3%	0.8%	15.3%
	Average (min)	23.6	67.9	30.1	62.5
	Trip share	**100%**	**1.7%**	**7.2%**	**0.1%**
	Observations	124,262	2,328	8,843	178
	Estimated trip number	41,113,003	692,889	2,979,994	58,062
	Sample penetration rate	0.302%	0.336%	0.297%	0.307%

Table C.7 – Trip variables effects on intermodality for Paris region subpopulations

Paris region trip legs

Trip leg length	Walk	PT	Taxi	Interurban	Car	Motorcycle	Bike	Other	
	Trip leg mode								
60m	37.8%	0.0%			0.0%	0.0%	0.0%	0.0%	37.8%
61 to 200m	9.3%	0.1%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	9.6%
201 to 400m	9.2%	0.1%	0.0%	0.0%	0.6%	0.0%	0.0%	0.0%	10.0%
400 to 750m	7.3%	0.7%	0.0%		1.6%	0.0%	0.1%	0.0%	9.7%
751 to 1400m	3.1%	2.3%	0.0%	0.0%	2.4%	0.1%	0.2%	0.0%	8.0%
1401 to 2600m	0.7%	3.4%	0.0%	0.0%	2.8%	0.1%	0.2%	0.0%	7.1%
2601 to 5000m	0.2%	3.4%	0.0%	0.0%	2.8%	0.1%	0.1%	0.0%	6.6%
5001 to 10000m	0.0%	2.4%	0.0%	0.0%	2.7%	0.1%	0.0%	0.0%	5.3%
Over 10000m	0.0%	2.2%	0.0%	0.0%	3.0%	0.1%	0.0%	0.0%	5.3%
N/A	0.3%	0.0%	0.0%	0.1%	0.2%	0.0%	0.0%		0.5%
	67.7%	14.5%	0.1%	0.1%	16.2%	0.6%	0.7%	0.1%	100%
Average length (km)	0.2	5.6	8.2	27.0	6.1	6.4	1.9	1.4	

Paris region intermodal trip legs

Trip leg length	Walk	PT	Taxi	Interurban	Car	Motorcycle	Bike	Other	
	Trip leg mode								
60m	21.1%	0.0%			0.0%		0.0%		21.1%
61 to 200m	6.8%	0.1%		0.0%	0.1%		0.0%	0.0%	7.1%
201 to 400m	7.7%	0.2%	0.0%	0.0%	0.4%		0.1%	0.0%	8.5%
400 to 750m	5.5%	1.2%			1.5%	0.0%	0.3%	0.1%	8.6%
751 to 1400m	1.7%	4.0%		0.0%	3.1%	0.0%	0.7%	0.1%	9.6%
1401 to 2600m	0.3%	4.9%	0.0%	0.0%	4.5%	0.1%	0.5%	0.0%	10.4%
2601 to 5000m	0.0%	6.1%	0.0%	0.0%	2.5%	0.0%	0.1%	0.0%	8.8%
5001 to 10000m	0.0%	5.6%	0.0%	0.0%	2.1%	0.0%	0.0%		7.8%
Over 10000m		13.3%	0.0%	0.5%	1.4%	0.0%			15.2%
N/A	1.4%	0.0%		1.3%	0.1%				2.9%
	44.6%	35.3%	0.1%	1.9%	15.7%	0.2%	1.9%	0.3%	100%
Average length (km)	0.2	10.6	6.9	27.6	4.0	2.8	1.4	0.8	

Study population trip legs

Trip leg length	Walk	PT	Taxi	Interurban	Car	Motorcycle	Bike	Other	
	Trip leg mode								
60m	30.0%	0.0%			0.0%	0.0%	0.0%		30.1%
61 to 200m	10.6%	0.1%			0.1%	0.0%	0.0%	0.0%	10.8%
201 to 400m	10.4%	0.1%	0.0%		0.2%	0.0%	0.0%	0.0%	10.8%
400 to 750m	7.8%	1.0%			0.5%	0.0%	0.0%	0.0%	9.4%
751 to 1400m	3.6%	3.3%			1.4%	0.1%	0.3%	0.0%	8.6%
1401 to 2600m	0.9%	4.9%	0.0%		2.0%	0.1%	0.2%	0.0%	8.1%
2601 to 5000m	0.2%	5.5%	0.0%		2.1%	0.2%	0.2%		8.1%
5001 to 10000m	0.0%	4.3%	0.0%		2.5%	0.2%	0.1%	0.0%	7.1%
Over 10000m		3.0%	0.0%	0.0%	3.2%	0.1%	0.0%		6.4%
N/A	0.3%			0.1%	0.1%				0.6%
	63.6%	22.2%	0.1%	0.2%	12.3%	0.7%	0.8%	0.1%	100%
Average length (km)	0.3	5.4	11.2	47.8	7.8	6.1	2.3	0.9	

Table C.8 – Trip leg mode and trip leg mode choice bivariate distributions

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