



# Values of Time for Carpool Commuting with HOV lanes: A Discrete Choice Experiment in France

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*Keywords: Values of Time, Carpool, Commuting Trips, HOV-lane, Discrete Choice Experiment*

*J.E.L. Classification: R41, C35*



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# Values of Time for Carpool Commuting with HOV-lanes: A Discrete Choice Experiment in France

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## ABSTRACT

We conduct a discrete choice experiment on 931 solo-driving commuters in Lyon, France to estimate the values of end-to-end travel time (VoTT) in the presence of an HOV lane for four modes: Solo Driver, Carpool Driver, Carpool Passenger and Public Transport. Mixed and latent class logit models are estimated. We find that Carpool Passenger, Carpool Driver and Public Transport median VoTTs are respectively around 20%, 40% and 60% higher than Solo Driver VoTT. The analysis of individual heterogeneity distinguishes three classes of behavior in our sample: open to carpool as a driver (41%), open to passenger modes (32%) and resistant to all alternatives to solo driving (28%). These three categories allow to identify solo drivers who could switch to carpool as drivers. We show that encouraging current solo drivers to switch to carpool as passengers will be more sensitive if public transport services are also improved.

**Keywords:** Values of Time; Carpool; Commuting Trips; HOV-lane; Discrete Choice Experiment

Declarations of interest: none

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## 1. INTRODUCTION

Traffic congestion is still a major issue in large cities around the world. France is no exception to this observation. According to [INRIX \(2018\)](#), the drivers in Paris, Marseille, Lyon and Toulouse – the four largest cities in the country – respectively lost on average 237, 140, 141 and 130 hours in road congestion in 2018. Most of this traffic congestion appears during morning and evening peak hours.

Promoting carpool is seen as a cost-effective way to moderate road congestion while avoiding costly investments in road expansion and also to reduce harmful gas emissions. As USA recently experienced an increase in solo driving in commuting modal share ([AASHTO, 2013](#)), the objective here is to increase car occupancy rate. There is a clear room for improvement as the current rate is low in France, between 1.2 and 1.3 individuals per vehicle on average for weekday trips ([ENTD, 2008](#)). This occupation rate falls at 1.08 for commuting trips. Similar results are found in UK<sup>2</sup>, USA<sup>3</sup> or Australia<sup>4</sup>. It implies that there is a large unused transport capacity during peak hours.

Local policy makers in France currently consider different kinds of policies to promote carpool for commuting trips. The cities of Lyon and Grenoble are expected to experiment HOV-lanes in 2020. These lanes are expected to reduce travel time and to increase travel time reliability for carpoolers. The Ile-de-France (Paris) Region gives monetary incentives to carpool drivers (between 1.5 and 3 euros per trip), and free public transport tickets for carpool passengers. Several regions have developed a carpool web platform to ease the matching between drivers and passengers. Private companies are also encouraging their employees to carpool. Moreover, Vinci, a toll motorway company, has launched a partnership with Blablacar, the world number one carpool company (see [Shaheen et al. 2017](#)). Vinci's subscribers carpooling on the motorway benefit from lower management fees on the BlaBlaCar platform.

Promoting a successful carpool policy needs a better understanding and measure of carpool trips attributes. In a state-of-the-art of ridesharing<sup>5</sup>, [Furuhata et al. \(2013\)](#) emphasized how route and time matching issues between drivers and passengers can be very constraining, even in a simple situation. They also identify different classes of carpools/rideshares and hence different constraints and/or advantages for each one. [Chaube et al. \(2010\)](#) conducted a survey in an American university and found that a close relationship between carpoolers was a key factor of successful ride-matching: 98% of students would accept to carpool with a friend, 69% with a friend of a friend, but only 7% would accept a ride with a person they do not know. Gender and age differences in the car party are also issues involved. However, in spite of several studies identifying obstacles to carpool, we did not find evidences of carpool-specific values of travel time in the literature.

This paper aims to fill this gap. We address the following research questions: what are the values of travel time (VoTT) as a carpool driver or passenger? Are these values different from the values for a

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<sup>2</sup>[https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\\_data/file/457752/nts2014-01.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/457752/nts2014-01.pdf)

<sup>3</sup> <https://nhts.ornl.gov/2009/pub/stt.pdf>

<sup>4</sup> <https://chartingtransport.com/2011/08/20/whats-happening-with-car-occupancy/>

<sup>5</sup> In the following we use indifferently “carpooling” or “ridesharing”.

trip made as a solo driver or a public transport user? How are the values distributed across the commuter population?

We answer these questions by estimating end-to-end VoTT and their distributions for commuting trips as a solo driver, a carpool driver, a carpool passenger and a public transport passenger. End-to-end travel time (or total travel time) are valued in this paper to compare values found for carpool to the existing values for car. This choice is made even though times can be valued differently in a trip – like walk or wait – like [Wardman \(2016\)](#) showed for public transport. To this aim, a discrete choice experiment survey is conducted on a sample of 931 commuters using their car to commute in the city of Lyon. We use mixed and latent class logit models to consider the panel structure of our data and the heterogeneity of commuters.

Results are of interest for several reasons. To our knowledge, we are the first to empirically measure and value the time attributes of carpool commuting and to compare these values with those for usual modes. Hence, this paper contributes to the literature by estimating mode-specific values of time. Furthermore, the analysis of individual heterogeneity could allow public policies to target the profiles of drivers most likely to switch from solo driving to carpooling and provide information on potential subsidies to encourage this switch. We produce estimations of carpool-specific values of time which can be used in transport forecasting models. They could also be used as prior values to establish official guidelines in cost-benefit analysis. Finally, carpool matching platforms could be interested in our estimations and in our latent class models to implement market differentiation.

The rest of the paper is organized as follows. Section 2 below is a literature review of carpooling issues and VoTT surveys. Section 3 presents the survey design, data sampling and summary statistics. Section 4 shows the methodological framework and the empirical strategy used to estimate values of time. Section 5 presents the results, which are discussed in Section 6 and Section 7 concludes.

## 2. LITERATURE REVIEW

### 2.1 Carpool for commuting and HOV-lanes

Even though the French company Blablacar substantially promoted carpooling for long distance trips, this mode is still rarely used in France on a daily basis<sup>6</sup>. Several constraints may explain this fact.

The matching process appears to be more difficult for daily carpool than it is for occasional long-distance carpool trips. More specifically, compared to long-distance carpool, schedule and spatial (i.e. nearby origins and nearby destinations) constraints in daily carpool have an increased role in the matching between driver and passenger. As the trip is shorter than in long distance, detour time, waiting time, access or egress times represent a higher part of the end-to-end travel time. So, the temporal and spatial match between a driver and a passenger has to be almost perfect to avoid this time loss. In a state-of-the-art on ridesharing, [Furuhata et al. \(2013\)](#) showed how quickly matching can be problematic when a driver and several passengers have to match at different times and places. They show that optimal

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<sup>6</sup> The modal share of carpooling for medium-distance commuting (20 to 80 km) in France is estimated around 10% (ADEME, 2015)

1 matching situations (which allow each passenger to find a driver and vice versa) are not always easily  
2 achievable.

3 In addition to these matching issues and similarly to long-distance carpool, daily carpooling raises the  
4 question of trust between carpoolers. Trust is a key element to give or take rides from others (Chaubé et  
5 al., 2010). Chan & Shaheen (2012) made a review of ridematching programs in North America.  
6 Individuals often consider carpooling as a risky mode. The desire of independency or flexibility are also  
7 reasons raised from solo drivers to stay alone in their car (Li et al., 2007).

8 In a Texan survey (Li et al., 2007) and a French survey (ADEME, 2015), carpoolers often cite  
9 friendliness, ecology or a reduced stress and fatigue – in addition to economic criteria – as reasons why  
10 they choose this mode. Intuitively, the economic gain or loss is an essential attribute in the transport  
11 modal choice. Sharing the costs makes carpooling economically competitive compared to solo driving.  
12 Some incentives can also make individuals change their transport mode choice, like “parking cash-out”  
13 experienced in California Shoup (1997), or “positive toll” concept tested in Rotterdam<sup>7</sup>. Results showed  
14 an increase of carpoolers in the first experiment and a reduction of traffic in the second.

15 Another incentive to carpool is to implement lanes reserved to high occupancy (HOV) lanes which offer  
16 time savings to carpoolers. Necessary criteria for their proper functioning have been mentioned by  
17 Schijns & Eng (2006) and Chan & Shaheen (2012). The HOV-lane has to be used by an important  
18 number of people to avoid the “empty lane” phenomenon and to gain acceptance from the population.  
19 It should give significant and reliable travel-time savings. An efficient HOV-lane should increase the  
20 number of people using the corridor. Several studies showed these lanes can be effective, like in New  
21 York where Ugolik et al. (1996) measured HOV-lanes increased the number of people in the vehicles  
22 by 14%. In their survey and focus groups, they also found both HOV users and non-users support an  
23 extension of the HOV-lane. Other surveys also demonstrate HOV-lanes can have a positive impact on  
24 traffic too. Traffic measurements on several HOV<sup>-</sup> lanes in San Francisco Bay Area conducted by  
25 Daganzo & Cassidy (2008) show that HOV-lanes that does not create new bottlenecks add very few  
26 vehicular delay (i.e. the average time spent crossing the corridor), around 2% and reduce people delay  
27 by more than 10%.

28 These past results suggest public policies should focus on three main attributes to convince people to  
29 carpool: monetary gains, time savings and building trust.

## 30 **2.2 Values of Travel Time Heterogeneities**

31 Sensitivities for monetary gains and time savings and more precisely their ratio (value of travel time,  
32 VoTT) are very discussed in the transport economics literature. This high consideration is due to their  
33 usage in both the evaluation of transport projects - to calculate the social welfare - and also the  
34 understanding of individual's mode or route choices. In a paper entirely devoted to VoTTs, Small (2012)  
35 discussed VoTT heterogeneity found in the literature. This heterogeneity depends on various elements  
36 such as trip purpose, discomfort in a transportation mode, traffic conditions, trip duration. However, this

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<sup>7</sup> [https://www.rse-egis.fr/en/solution\\_egis/positive-tolls/](https://www.rse-egis.fr/en/solution_egis/positive-tolls/)

paper suggests that a wide part of these heterogeneities remains misunderstood and hence depends on individual unobserved characteristics.

The empirical results show indeed a large heterogeneity in VoTTs: [Jara-Diaz et al \(2008\)](#) showed through an analysis of work and leisure in three different countries (Chile, Switzerland and Germany), that the commuting VoTT is not the same between different countries. These results are confirmed by a worldwide meta-analysis proposed by [Shires & De Jong \(2009\)](#) and European meta-analyses (see [Wardman et al. 2012, 2016](#)). Their results suggest that VoTT is correlated less than proportionally to wage rate with income elasticities varying between 0.68 and 0.85. The heterogeneity of VoTT found in their different studies also depends on trip purpose and traffic conditions, they are higher in congested conditions than in free flow.

VoTTs appear heterogeneous also depending on the mode. [Wardman et al. \(2016\)](#) distinguished mode used – relative to individual characteristics – and mode valued – relative to mode characteristics such as comfort, privacy, security or externalities due to environment. Their findings show a mode valued difference between bus and car for commuting trips, with a significantly lower VoTT in car trips. Previous surveys tend to show that travel time values are lower for public transport users – in bus and rail – than for car users ([Shires & De Jong, 2009](#); [Wardman et al., 2012](#); [Quinet, 2013](#)). With regard to carpooling VoTT, in a SP survey, [Blayac & Adjeroud \(2018\)](#) compared VoTTs of bus and carpool users over long distances. They found that the value of time for carpool users is more than twice the one of bus users. [Monchambert \(2020\)](#), in a long-distance carpool survey, founds that VoTTs in carpooling are higher than those as a solo driver, bus user and train user.

Different modeling techniques are used to capture the individual heterogeneity. The most common is to use a mixed logit model that allows some attribute coefficients to be distributed throughout the population (e.g. [Hess et al., 2005](#)). In our case, cost and time individual sensitivities are examined to determine VoTT. However, several issues may appear as shown in [Daly et al \(2012\)](#) to determine the ratio of two distributions. A solution is to use WTP space (see [Train & Weeks, 2005](#)) to solve the problem. Multiplying the cost coefficient with time coefficients allows to estimate only one distribution. Other discrete choice models allow alternative evaluations of heterogeneity and may simplify their interpretation. A complementary modelling and interpretation of individual heterogeneity can be provided through a latent class logit model, in which the sample is considered as represented by several classes, each one having different sensitivities (see e.g. [Greene and Hensher, 2003](#); [Shen et al., 2006](#)).

### 3. SURVEY DESIGN AND DATA SAMPLING

A discrete choice experiment is designed to collect data to examine the trade-off between travel time, delays and cost (or gain) for trips as a driver or as a passenger. This experiment has been conducted through a responsive questionnaire described below.



### 3.1 Study context

This questionnaire was designed to observe how the inhabitants of the Lyon area (1.4M inhabitants) would react to the creation of a HOV-lane, a new infrastructure in France<sup>8</sup>. Indeed, the City of Lyon is going to set up two HOV-lane sections on its main North-South axis, allowing shorter and more reliable travel times for carpoolers than for solo drivers. These lanes will be 6 and 4-km long for the northern and the southern sections respectively. The expected time savings for carpoolers are between 5 and 10 minutes during morning rush hours.

### 3.2. Survey design

The questionnaire is organized in three parts. The first part aims at collecting basic socio-demographic data and the trip characteristics. The second part is the stated choice experiment. It is a dynamic experiment in the sense that the choices tasks proposed to the respondent depend on her trip characteristics. The third part is a questionnaire on attitudes.

#### *First part: socio-demographic and trip characteristics*

We first collect information on socio-economics variables of the respondent (gender, age, income, professional position...) and on the characteristics of their “usual trip” i.e. the most frequent trip made by public transport or car. These characteristics will be used to responsively build the choice tasks in the second step of the survey.

Our aim is to place the respondent in the context of a trip he can do with the proposed modes in the survey. For very short distance trips (<15 minutes by car), we consider carpooling is not a credible alternative. Even a short waiting time (for the passenger) or detour time (for the driver) would proportionally lengthen the trip a lot. On the other hand, trips longer than 90 minutes were also considered as too long for carpooling, the time gain procured by the HOV-lane could be proportionally too short to be convincing to change mode. Furthermore, the average commuting time by car in Lyon area is around 30 minutes<sup>9</sup> and the longer the trip the harder it would be to find a carpooler far from the city center. Consequently, only respondents whose usual trip meets the following criteria are kept in the survey:

- a travel time between 15 and 90 minutes
- driving their car
- during rush hours (between 6 and 10 am or between 4 and 8 pm, excluding weekends)

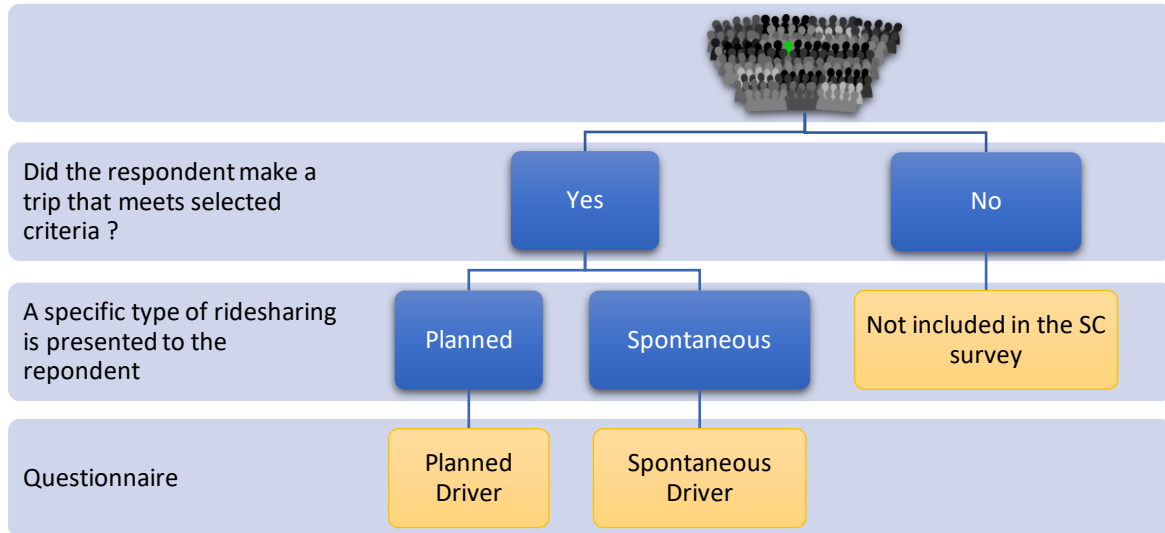
The respondent is then randomly assigned to one of two kinds of carpool organization (planned or spontaneous). Planned carpool implies meeting place and time schedule arranged before the trip starts.

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<sup>8</sup> As HOV-lane is not a common infrastructure in France, we introduced in the survey a screen presenting this infrastructure.

<sup>9</sup> We remind the average commuting time by car is inferior to 30 minutes in Lyon : [https://www.scot-rivesdurhone.com/wp-content/uploads/2016/08/EnqDeplcmt2015\\_plaq\\_generale\\_27062016\\_120dpi\\_pourWEB.pdf](https://www.scot-rivesdurhone.com/wp-content/uploads/2016/08/EnqDeplcmt2015_plaq_generale_27062016_120dpi_pourWEB.pdf)

It can be organized by carpooling platforms or informally with family, friends or colleagues. In spontaneous carpool, carpoolers can meet up without prearrangement in a carpool station or along the road. This includes hitchhiking or so-called dynamic carpooling through digital apps which fix a meet up in real time. Respondents are faced with a screen explaining the kind of carpool organization depending on their assignment. As it is a new infrastructure in France, the HOV-lane is also presented before the choice tasks to the respondents through a screen.



**Figure 1:** Data sampling and survey protocol

### Second part: Experimental Design

We want respondents to make the same choices they would do in a real situation. To do so, choices are kept realistic in the respondents' mind by using the information on their usual trip collected earlier. The time attributes levels are adapted in order to propose to respondents different alternatives in which travel duration and arrival times vary around their current values.

It is important that the attribute levels of the proposed alternatives are not such that any alternative strongly dominates the others (Hensher & Rose, 2015).

Since variation is needed between the various exercises, a total of 60 different choice task patterns is created, split into 10 blocks. Then each respondent is allocated to a block and faced with 6 choice situations. The choice sets vary depending on the information about her usual trip collected in the first part of the survey. In each of these choice screens, the respondent has the choice between 4 alternatives (modes): Solo Driver, Carpool Driver, Carpool Passenger and Public Transport (see Appendix A). Furthermore, the order of columns is randomized for each screen to avoid the left right bias as recommended by Hess & Rose (2009).

For a given trip, each alternative is characterized by different types of variables.

-Trip characteristics include several time variables as well as the departure and arrival times.

-The monetary aspects includes two attributes. The first monetary attribute represents the usual cost of the solo driver that he can potentially save in passenger modes, presented by "You pay(in driver

modes)/save on(in passenger modes) your usual transportation cost” in the choice screens. The second attribute is the price paid for a ride in public transport or in carpool as a passenger. It may also represent the gain earned in carpool as a driver.

-In carpool alternatives, matched carpooler’s profile is also presented in order to check for other attributes who could affect mode choice such as close relationship between driver and passenger. Even though these variables are expected to affect mode choice, we will mainly focus on time and monetary aspects in this paper.

The Ngene software ([ChoiceMetrics, 2012](#)) is used with a D-efficient design (see Rose et al., 2008) to build balanced choice tasks without dominated or dominant alternatives. The efficient design allows to avoid strong dominance of one mode on another. For that, prior information about parameters have been used from [de Palma and Fontan \(2000\)](#) and [Quinet \(2013\)](#). The mode attributes and levels used in the choice tasks are presented in Table 1.

**Table 1:** Trip attributes and levels in stated choice design

Attributes	Alternatives	Levels
<b>Time variables</b>		
Schedule early/late	Solo Driver	0, 30, 60 minutes (earlier or later)
End-to-end travel time (in min)	Solo Driver	Min: $0.8 * usual\_tt$ Max: $1.9 * usual\_tt$
	Carpool Driver	Min: $0.6 * usual\_tt$ Max: $1.5 * usual\_tt + 20$
	Carpool Passenger	Min: $0.6 * usual\_tt + 10$ Max: $1.5 * usual\_tt + 50$
	Public Transport	Min: $0.6 * usual\_tt + 10$ Max: $1.5 * usual\_tt + 35$
<b>Cost</b> (in €)	Carpool Driver	Receives $(0, 0.02, 0.05, 0.1) * usual\_tt$
	Carpool Passenger	Pays $(0, 0.02, 0.05, 0.1) * usual\_tt$
	Public Transport	Pays 0.8
<b>Carpooler profile</b>		
Carpooler matching	Carpool Driver and Carpool Passenger	Planned, Spontaneous
Carpooler Gender		Male, Female (not presented if relative)
Carpooler Age		25, 45, 65 years old (not presented if relative)

*Notes: Passenger modes: Carpool Passenger and Public Transport. Carpool modes: Carpool Driver and Carpool Passenger. “usual\_tt” is the usual travel time the respondent reports in the survey. Detailed attribute levels are provided in Appendix D.*

### Third part: Attitude Questions

Finally, five questions are asked to evaluate the respondent’s sensitivity to environmental consequences of the solo driving practice. Indeed, incentivizing carpooling involves psychological and social dimensions which go beyond self-interest, this latter dimension being covered through our DCE design.

1 The environment or the level of congestion in the city may be seen as “commons” which deserve specific  
2 behavioral adaptations.

3 Regarding the potential of motivational factors towards pro-environmental behavior, the literature offers  
4 two main theories. The one is based on self-perceived cost and benefits, with the theory of planned  
5 behavior (TPB; [Ajzen, 1991](#)). TPB aims at explaining behavioral intentions (viewed as the immediate  
6 antecedent of actual behavior) by the attitudes (ATT), the perceived social pressure regarding this  
7 behavior (subjective norms, SN) and the perceived behavioral control (PBC). The other theory is based  
8 on moral and normative concerns with the norm-activation theory (NAT; Schwartz, 1977) and aims at  
9 explaining altruistic behavior. Feelings of obligation, stemming from perceived norms (PN), precede  
10 immediately behavior and are activated by the awareness of behavior consequences (AC) and beliefs  
11 about personal responsibility.

12 These two theories are applied and compared by [Wall et al. \(2007\)](#) in order to explain drivers' intentions  
13 to reduce or maintain their car use for commuting. The authors show that a combination of TPB and  
14 NAT constructs has a superior power of explanation when compared to the two theories separated.  
15 Following Wall et al. conclusions we build a set of five statements (presented on a Likert scale) which  
16 cover the basic constructs of both theories:

17 1: Car traffic is a major source of pollution and congestion (AC).

18 2: I am satisfied with my daily trip choices (ATT).

19 3: I can or could easily change the way I travel on a daily basis (PBC).

20 4: The opinion of people who matter to me is important for the way I travel on a daily basis (SN).

21 5: I feel personally responsible for contributing to reduce pollution and congestion (PN).

### 22 **3.3. Data**

23 Data was collected from an online survey. A partnership with different motorway companies, local  
24 authorities, University of Lyon and a carpool-specialized company allowed us to spread a web-link of  
25 the survey to many inhabitants in the Lyon area. There was a financial incentive to answer the survey  
26 as respondents had a chance to win a 100€ voucher. A wide part of the sample came thanks to the  
27 dissemination of the survey to electronic tolling motorway subscribers. Finally, a database containing  
28 around 3,300 respondents who fully completed the survey was collected.

29 In this paper our focus is on the potential change of daily commuters from solo-driving to carpooling  
30 when facing an HOV-lane. Thus, only respondents who declare an usual trip as solo drivers, at least  
31 several times a week and for work purpose are kept. This commuters' subset still represents an important  
32 part of our base sample, with 2,044 respondents.

33 Finally, some adhoc data filtering is applied as recommended by [Hess et al. \(2010\)](#). Since response times  
34 for each choice screen are available, people who answered to a choice screen at least once in less than 6  
35 seconds are excluded. This allows us to remove respondents who only came to win a voucher and answer

the questionnaire as fast as they can without examining the choice sets. Furthermore, we considered as our respondents are currently solo drivers, they should at least select Solo Driver mode once, to get close from their revealed preferences. This filtering is detailed in Appendix C.

The final sample meeting criteria includes 931 individuals. Descriptive statistics of this final sample are presented in

Table 2 below.

**Table 2:** Sample characteristics

	Planned Carpool experiment		Spontaneous Carpool experiment		Total	
	Mean	sd	Mean	sd	Mean	sd
<b>Individual</b>						
Male	56.2%		55.6%		55.9%	
Age (years)	45.0	10.4	45.5	10.5	45.3	10.5
Income per month (€)	2329	882	2389	904	2359	894
Occupation						
Self-employed	4.8%		4.7%		4.7%	
Senior Management/Professional	45.6%		46.8%		46.2%	
Middle Management	12.3%		11.3%		11.8%	
Clerical Staff	32.6%		33.8%		33.2%	
Laborers	3.9%		3.0%		3.4%	
Students	0.9%		0.4%		0.6%	
<b>Reference trip</b>						
Length (min.)	40.0	17.5	39.7	17.5	39.8	17.5
<b>Attitude statements (in the whole sample)</b>	Strongly Dis.	Disagree	Neutral	Agree	Strongly Agr.	
S1 (“car traffic major source”)	2.9%	6.3%	9.9%	37.9%	43.0%	
S2 (“satisfied with my choices”)	5.9%	20.1%	18.4%	34.4%	21.3%	
S3 (“could change easily”)	25.3%	29.6%	16.5%	23.3%	5.2%	
S4 (“opinion matter”)	27.4%	17.6%	32.1%	16.2%	6.7%	
S5 (“personally responsible”)	7.3%	10.0%	27.1%	40.9%	14.7%	
<b>Nb of individuals</b>	463		468		931	

*Notes: income variable is collected as categorical. Mean and standard deviation are calculated using the center of the classes selected by respondents.*

## 4. METHODOLOGY

### 4.1. Econometric Models

Three models are used to analyze the discrete choice data: a multinomial logit (MNL) which is the usual base model, a mixed logit (MXL) and a latent class logit (LCL). The last two models allow to consider the panel structure of the data and individual heterogeneity in sensitivities for some attributes (Lancsar et al., 2017).

# *Multinomial Logit (MNL)*

The probability to choose  $j$  among the  $K$  alternatives available for individual  $i$  in MNL can be written:

$$P_{ij} = \frac{\exp(X_{ij}\beta_j)}{\sum_{k=1}^K \exp(X_{ik}\beta_k)} \quad (1)$$

where  $X$  designate characteristics of the observable part of the utility and  $\beta_k$  are the model's estimates for alternative  $k$ .

Nonetheless, this model has some limitations such as the Independence of Irrelevant Alternatives (IIA) assumption. Therefore, MXL and LCL models have been proposed in the literature to allow for individual heterogeneity between the respondents and to release the IIA assumption (see e.g. [McFadden & Train, 2000](#); [Greene & Hensher, 2003](#)).

# *Mixed Multinomial Logit (MXL)*

The MXL model allows for heterogeneity through "random parameters" estimates the analyst can define. The difference with the MNL is that the  $\beta_k$  estimates become  $\beta_{ik}$ , varying through individuals and following a distribution chosen by the analyst.

Following [Train \(2009\)](#) the mixed logit probabilities are the integrals of standard logit probabilities over a density of parameters.

$$P_{ij} = \int L_{ij}(\beta)f(\beta)d\beta \quad (2)$$

where  $f(\beta)$  is a density function and  $L_{ij}(\beta)$  the logit probability evaluated at  $\beta$  such that

$$L_{ij}(\beta) = \frac{\exp(V_{ij}(\beta))}{\sum_k \exp(V_{ik}(\beta))} \quad (3)$$

This specification is extended to take account of  $T$  repeated choices by each individual in the sample. The utility for individual  $i$  in choice situation  $t$  becomes:

$$U_{ijt} = \beta_{ij}X_{ijt} + \varepsilon_{ijt} \quad (4)$$

and

$$P_{ij} = \int \prod_{t=1}^T \frac{\exp(\beta_{ij}X_{ijt})}{\sum_k \exp(\beta_{ik}X_{ikt})} f(\beta)d\beta \quad (5)$$

We assume individuals cannot enjoy travelling longer. Hence, lognormal distributions are estimated for all time attributes to avoid negative values of time.

## Latent Class Logit (LCL)

Contrary to the MXL, the LCL model does not need any assumption on distribution of preferences in the population. This model assumes that the sample is implicitly separated into  $Q$  “latent” classes characterized by homogenous intra-class preferences. Estimates for a same attribute are then different between classes but remain fixed in each. The number of classes is defined by choosing the model with the lowest AIC (Louviere et al. 2000, chap.10).

The probability to choose  $j$  among the  $K$  alternatives available for an individual  $i$  in class  $q$  in LCL can be written:

$$P_i(j|q) = \frac{\exp(X_{ij}\beta_q)}{\sum_{k=1}^K \exp(X_{ik}\beta_q)} \quad (6)$$

with  $\beta_q$  estimates fixed for each class, but different through classes.

Hence, given  $\pi_{iq}$  the probability for an individual  $i$  to belong to class, we have:

$$P_{ij} = \sum_{q=1}^Q \pi_{iq} \prod_{t=1}^T P_i(j|q) \quad (7)$$

Where  $\pi_{iq}$  is calculated through a class allocation logit model such as:

$$\pi_{iq} = \frac{\exp(Z_i\gamma_q)}{\sum_{c=1}^Q \exp(Z_i\gamma_c)} \quad (8)$$

Concerning the parametrization of latent classes, we let intercepts and time estimates vary through the classes. Other variables remain fixed across all classes just like in the MNL model.

Furthermore, the analyst can define latent class parameters to explain the class allocation probability of individuals (see Hess & Palma, 2020). Hence, we tried to use the “sensitivity to environment” answers as explanators of the classes.

## 4.2. Generalized Costs Specifications

In this paper, the focus is on the valuation of different time variables presented to the respondent. We use a willingness to pay space (WTP) utility specification as presented first by Train and Weeks (2005). This expression of the utility is a re-parametrization, by multiplying the cost coefficient estimate by time coefficients. This specification allows for a direct interpretation of time estimates as values of time. The usual way to compute the willingness to pay for a given parameter is to divide this parameter estimate by the monetary cost estimate. However in a MXL, the monetary cost coefficient can be equal or close to 0, depending on the chosen distribution. This leads to non-defined or infinite willingness to pay. As suggested by Daly et al. (2012), WTP-Space is certainly the most straightforward way to treat this issue.

Utilities for the four alternatives are presented below.

$$V_{D_{solo}} = \beta_{0ds} + \beta_{cost}(Cost_{ds} + \beta_{tt ds} TT_{ds} + \beta_{earl} SchedEarly + \beta_{late} SchedLate) + \beta_{Z ds} Z$$

$$V_{D_{carpool}} = \beta_{0 dcp} + \beta_{cost}(Cost_{dcp} + \beta_{tt dcp} TT_{dcp}) + \beta_{Z dcp} Z + \beta_{CPO dcp} CPO_{dcp}$$

$$V_{P_{carpool}} = \beta_{0 pcp} + \beta_{cost}(Cost_{pcp} + \beta_{tt pcp} TT_{pcp}) + \beta_{Z pcp} Z + \beta_{CPO pcp} CPO_{pcp}$$

$$V_{PubTransport} = \beta_{0 pt} + \beta_{cost}(Cost_{pt} + \beta_{tt pt} TT_{pt}) + \beta_{Z pt} Z$$

(9)

where  $ds$ ,  $dcp$ ,  $pcp$  and  $pt$  represent respectively the four alternatives: Solo Driver, Carpool Driver, Carpool Passenger and Public Transport, respectively.  $Cost$  is the cost attribute,  $TT$  is the total travel time (end-to-end travel time). It regroups in-vehicle travel time, access time, waiting time, detour time and egress time.

$\beta_{0k}$  is the Alternative Specific Constants (ASCs) associated with mode  $k$ ,  $\beta_{cost}$  is the cost coefficient,  $\beta_{ttk}$  the Value of Time of mode  $k$ ,  $Z$  the individual variables and  $CPO$  the carpool organization variables.  $\beta_Z$  and  $\beta_{CPO}$  are vectors of estimates for  $Z$  and  $CPO$  respectively.  $\beta_{0ds}$  and  $\beta_{Zds}$  are fixed to 0 as references.

At this point, it might be useful to recall that we expect VoTT to vary across individuals, but that we also expect VoTT of one individual to vary across modes, due to differences in comfort or safety. Therefore one VoTT coefficient per mode is estimated.

Focusing on the Solo Driver cost function, leaving earlier or later is considered as an option to avoid road congestion.  $SchedEarly$  and  $SchedLate$  are schedule delay time variables.  $\beta_{earl}$  and  $\beta_{late}$  are their respective values. The  $Cost$  variable is null for this alternative as it represents the cost difference between the alternative and the Solo Driver situation (reference).

The schedule delay time variables indicate if the arrival time proposed differs from the respondent's preferred one.

In the MXL, travel time random parameters are defined as follows for mode  $k$ :

$$\beta_{ttk} = \exp(\mu_{\beta_{ttk}} + \sigma_{\beta_{ttk}} * \xi_{\beta_{ttk}})$$

(10)

where  $\mu$  and  $\sigma$  are the estimated parameters of the lognormal distribution and  $\xi$  follow standard normal distribution across individuals.

We also introduce correlations between travel time random parameters in a second MXL model (this one will be called MXL2 and the one without correlation will be called MXL1). In this model, the  $\beta_{ttk}$  estimates are assumed log-normally distributed with the following correlations:

$$\begin{aligned} \beta_{tt ds} &= \exp(\mu_{\beta_{tt ds}} + \sigma_{\beta_{tt ds}} * \xi_{\beta_{tt ds}}) \\ \beta_{tt dcp} &= \exp(\mu_{\beta_{tt dcp}} + \sigma_{\beta_{tt dcp}} * \xi_{\beta_{tt dcp}} \\ &\quad + \sigma_{dcp ds} * \xi_{\beta_{tt ds}}) \end{aligned}$$



$$\begin{aligned}
\beta_{ttpcp} &= \exp (\mu_{\beta_{ttpcp}} + \sigma_{\beta_{ttpcp}} * \xi_{\beta_{ttpcp}} \\
&\quad + \sigma_{pcpds} * \xi_{\beta_{ttds}} \\
&\quad + \sigma_{pcpdcpc} * \xi_{\beta_{ttdcpc}}) \\
\beta_{ttpt} &= \exp (\mu_{\beta_{ttpt}} + \sigma_{\beta_{ttpt}} * \xi_{\beta_{ttpt}} \\
&\quad + \sigma_{ptds} * \xi_{\beta_{ttds}} \\
&\quad + \sigma_{ptdcpc} * \xi_{\beta_{ttdcpc}} \\
&\quad + \sigma_{ptpcp} * \xi_{\beta_{ttpcp}})
\end{aligned} \tag{11}$$

Parameters  $\sigma_{dcpds}, \sigma_{pcpds}, \sigma_{pcpdcpc}, \sigma_{ptds}, \sigma_{ptdcpc}, \sigma_{ptpcp}$ , allow us to capture correlations between VoTT. As an example, the parameter  $\sigma_{dcpds}$  (used in the expression of  $\beta_{ttdcpc}$ ) is multiplied by  $\xi_{\beta_{ttds}}$ , already used in the expression of  $\beta_{ttds}$ . If  $\sigma_{dcpds}$  is positive, this means there is a positive correlation between the distribution of  $\beta_{ttds}$  and  $\beta_{ttdcpc}$  which implies that the higher the VoTT in Solo Driver mode is, the higher the VoTT for Carpool Driver mode is at an individual level (see [Hess & Palma 2020](#)).

## 5. RESULTS

First the multinomial and mixed logit estimates are presented, second the latent class logit estimates.

### 5.1 MNL and MXL models

Coefficients in Equations (9) are first estimated<sup>10</sup> with three models: a multinomial logit (MNL) described in Equation (1), and two mixed multinomial logits described in Equations (2) to (5), one without correlations (MXL1) one with correlations between travel time random parameters specified in Equations (11) (MXL2). These estimations include controls for the type of carpool organization used in the discrete choice experiment, for the carpool passenger characteristics (gender and age), and for the individual characteristics (income, gender and age). These controls are included respectively in Z and CPO variables in Equations (9). Full estimation results are displayed in Appendix B.

Estimation results are displayed in Table 3. The MXL1 and MXL2 models have been estimated with 1,000 Halton draws. In these models, the alternative-specific constants and the time coefficients are assumed to be normally and lognormally distributed, respectively.

Coefficients of interest are mode-specific. Consequently, a negative (resp. positive) coefficient implies a negative (resp. positive) marginal effect of the variable on the probability of choosing this specific mode over the others.

<sup>10</sup> The models have been estimated with the *Apollo* package built by [Hess & Palma \(2019\)](#) for the R software.

1 **Table 3:** Estimations results of MNL and MXL models

Attribute	Alternative	MNL	MXL1 (No Corr)	MXL2 (Corr)
Constants	Carpool Driver	-0.6594***	-0.9034*	-0.2655
	Carpool Passenger	-1.0646***	-1.4399**	-0.6139
	Public Transport	-1.2749***	-1.5419***	-1.0259
Time variables				
Total travel time (in €/min in MNL)	Solo Driver	0.3806***	-1.0922***	-0.8645***
	Carpool Driver	0.5126***	-0.7636***	-0.4354*
	Carpool Passenger	0.4564***	-0.9138***	-0.5192‘
	Public Transport	0.5347***	-0.6193***	-0.3472
Schedule late	Solo Driver	0.1237***	0.0812***	0.0824***
Schedule early	Solo Driver	0.1568***	0.1422***	0.1637***
Cost	All	-0.0861***	-0.1481***	-0.1350***
Standard deviations (in MXLs)				
sd Constants	Carpool Driver		-1.2882***	-0.4414*
	Carpool Passenger		-1.1924***	-0.9266***
	Public Transport		1.6304***	-1.4467***
sd Travel time	Solo Driver		-0.3438***	-0.8069***
	Carpool Driver		-0.3017*	0.4767***
	Carpool Passenger		-0.3196***	0.3900***
	Public Transport		-0.2675***	0.0558
Correlation estimates (in MXL2)				
Between modes	Solo Driver / Carpool Driver			-1.0892***
	Solo Driver / Carpool Passenger			-1.0451***
	Solo Driver / Public Transport			-0.7192***
	Carpool Driver / Carpool Passenger			0.4316***
	Carpool Driver / Public Transport			0.1259***
	Carpool Passenger / Public Transport			0.4102***
Carpool organization controls	Yes	Yes	Yes	Yes
Carpool Driver/Passenger controls	Yes	Yes	Yes	Yes
Individual characteristics controls	Yes	Yes	Yes	Yes
Nb of individuals	931	931	931	931
Nb of observations	5586	5586	5586	5586
Nb of parameters	29	36	42	42
LL(final)	-5931.2	-5263.9	-5125.7	-5125.7
Adj.Rho-square (0)	0.2303	0.3156	0.3327	0.3327
AIC	11920.4	10599.7	10335.3	10335.3
BIC	12112.6	10838.3	10613.7	10613.7

Notes: This table reports MNL and MXL estimates of coefficients in equations (1) to (4). Values for MXLs are the “ $\mu$ ” parameter of normal (for ASCs) and lognormal (for time) functions.

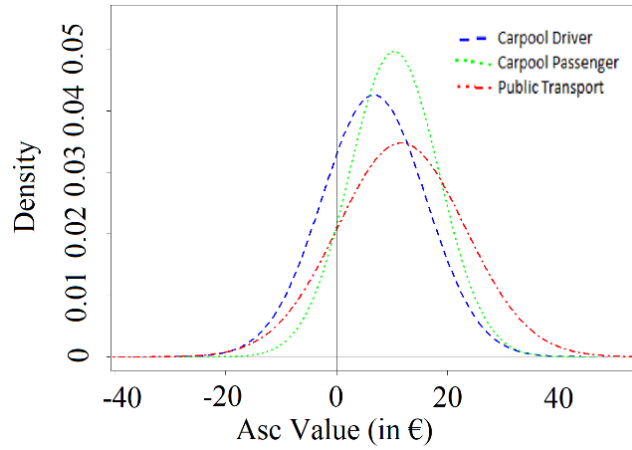
P-values: 1 ( ) 0.1 (‘) 0.05 (\*) 0.01 (\*\*) 0.001 (\*\*\*) 0. See Appendix B for more detailed results

## 2 General comments on models

3 The adjusted Rho-squared of our models go from 0.23 to 0.33 which shows a fairly good quality. The  
4 Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) confirm that using  
5 both random coefficients and correlations between time parameters produces a better goodness of fit.

## Constants

In MNL and MXL1, the alternative-specific constants (ASC) of all modes are significantly negative, Solo Driver being the reference. It means that all other variables equaling zero, there is on average a preference for Solo Driver mode over all the other modes. These preferences are high as the monetary equivalent<sup>11</sup> of the ASC in MNL go from 7.7€ (Carpool Driver) to 14.8€ (Public Transport). It means that on average and other variables equaling 0, an individual in our sample (i.e. a current solo driver) is willing to accept to switch to Public Transport if he receives at least 14.8€. The estimations of the ASC standard deviations in MXL1 and MXL 2 also show that these preferences are largely distributed across the population. Figure 2 illustrates this heterogeneity. The lower and upper quartiles of the Carpool Driver, Carpool Passenger and Public Transport passenger ASC distributions obtained from MXL1 are respectively [0.2, 12.0], [4.3, 15.2] and [3.0, 14.8].



**Figure 2:** Distribution of the monetary equivalent of ASC obtained from MXL1 across the sample

## Cost

As expected, the cost coefficient sign is negative in all specifications. The value of the estimated coefficient in MXL2 implies that all other things being equal, a 1 euro increase in the price of a mode decreases the odds of choosing this mode over other modes by 12.6%.<sup>12</sup>

## Values of time

The interpretation of the values of time is tricky because the specification varies between MNL, MXL1 and MXL2 (see Equations 10 and 11). Coefficients in MNL are the VoTT per minute, whereas coefficients in MXL1 and MX2 are  $\mu$  parameters of log-normal distribution of VoTT. Consequently, the median of the VoTT (per minute) distribution across the population is obtained by applying an exponential transformation to the estimated coefficient. Due to the specificities of the exponential function, the lower the coefficient is (included negative values), the lower the value of time is. For instance, on average, Solo Driver has the lowest VoTT. The VoTT standard deviation estimates in

<sup>11</sup> The monetary equivalent is computed by dividing the ASC by the cost coefficient.

<sup>12</sup>  $\exp(-0.1350) - 1 = -0.126$

1 MXL1 and MXL2 are significant. This means that VoTTs are distributed across the population and  
2 validates the assumption of heterogeneity.

3 The estimates of the  $\mu$  parameters of log-normal distribution of carpool passenger and public transport  
4 VoTT in MXL2 do not significantly differ from 0. However, the specification of these coefficients  
5 described in Equation (11) suggests that the VoTT are driven by the correlation between travel time  
6 parameters. We also observe that values of time are higher in MXL2 than in MXL1 (total travel time  
7 estimates are higher for the four modes, see Table 3). Introducing correlation between modes VoTTs  
8 reduces the impact of ASCs on preferences and by compensation increases the impact of VoTTs. Indeed,  
9 the estimates of correlation coefficients are significantly different from 0. Their interpretation is as  
10 follows: the coefficients comparing the Solo Driver mode and the others are negative, implying that  
11 people who value higher the time spent as a solo driver will tend to value lower time spent in other  
12 modes and vice versa. In contrast, the coefficients between the other modes are positively correlated,  
13 which imply people having higher valuation of time spent in one of these modes (carpooling and public  
14 transport) tends to value higher time in the other alternative modes to solo driving as well. We discuss  
15 and illustrate these results in the following section. The introduction of these estimates also partly  
16 explains why the Public Transport travel time parameter varies much less than others in MXL2 (see  
17 Table 3), because heterogeneity of values of time in this mode is already correlated to other  
18 heterogeneities in the three other modes.

#### 19 *Schedule delay*

20 Schedule delay is presented only with solo driving mode in the survey. In all models, the cost of arriving  
21 at destination one minute earlier than the preferred arrival time (0.16€/minute in MXL2) is found to be  
22 higher than the cost of arriving one minute later (0.08€/minute in MXL2). This is an unexpected result  
23 which will be discussed in the next section. Our results also suggest that the value of the schedule delay  
24 early is around 40% of the VoTT value.

#### 25 **5.2 LCL model**

26 We also estimate coefficients in Equation (9) with a latent class logit (LCL) model described in  
27 Equations (6) and (7). The lowest-AIC LCL model, presented here in Table 4, has three classes. We  
28 use the five “attitude statements”<sup>13</sup> as latent class membership covariates, as described in Equation (8).  
29 We also tested individual socio-economic variables (gender, age and income) as latent class  
30 membership covariates, but the goodness-of-fit was much lower.

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<sup>13</sup> The answers to these statements have been transformed into continuous variables as follows: -2 if the respondent strongly disagreed, -1 if disagreed, +1 if agreed and +2 if strongly agreed with the statement. Neutral answers were coded as 0.

1 **Table 4:** Estimations results of LCL model

Attribute	Alternative	LCL		
		Class A	Class B	Class C
Constants	Carpool Driver	0.4636**	-3.6684***	-0.7033**
	Carpool Passenger	-1.0196**	-3.1775*	0.3062
	Public Transport	-3.4962***	-6.6848***	0.6728**
Time variables				
Total travel time(in €/min)	Solo Driver	0.2581***	0.3223***	0.5538***
	Carpool Driver	0.3699***	0.5046***	0.6874***
	Carpool Passenger	0.2264***	0.6865*	0.6476***
	Public Transport	0.2187*	-0.0072	0.7023***
Schedule late	Solo Driver	-0.0394	-0.0533*	0.0595**
Schedule early	Solo Driver	0.3172***	0.1310***	0.1593***
Cost			-0.1097***	
Latent Class Allocation Variables				
Average Latent Class Allocation Probability		0.41	0.28	0.32
S1 (“car traffic major source”)		0	-0.1055	0.1165
S2 (“satisfied with my choices”)		0	0.3205***	-0.3498***
S3 (“could change easily”)		0	-0.4941***	0.2437**
S4 (“opinion matter”)		0	-0.1899*	-0.1622*
S5 (“personally responsible”)		0	-0.0541	-0.0544
Carpool organization controls			Yes	
Carpool Driver/Passenger controls			Yes	
Individual characteristics controls			Yes	
Nb of individuals			931	
Nb of observations			5586	
Nb of parameters			55	
LL(final)			-5027.3	
Adj.Rho-square (0)			0.3437	
AIC			10164.7	
BIC			10529.2	

Notes: This table reports LCL estimates of coefficients in equations (1) to (4).  
P-values: 1 ( ) 0.1 ( ) 0.05 (\*) 0.01 (\*\*) 0.001 (\*\*\*) 0. See Appendix B for more detailed results

2 *Latent class probability and covariates*

3 The sample average probability of belonging to Class A is 41%, 28% for Class B and 32% for Class C.  
4 We find that individuals who agree with the statements S2 (“I am satisfied with my daily trip choices”)  
5 and disagree with statement S3 (“I can or could easily change the way I travel on a daily basis”) have a  
6 higher probability of belonging to Class B. On the contrary, individuals who disagree with S2 and agree  
7 with S3 are more likely to belong to Class C. Finally, individuals who agree with S4 (“The opinion of  
8 people who matter to me is important for the way I travel on a daily basis”) are more likely to be in  
9 Class A.

10 *Mode preferences*

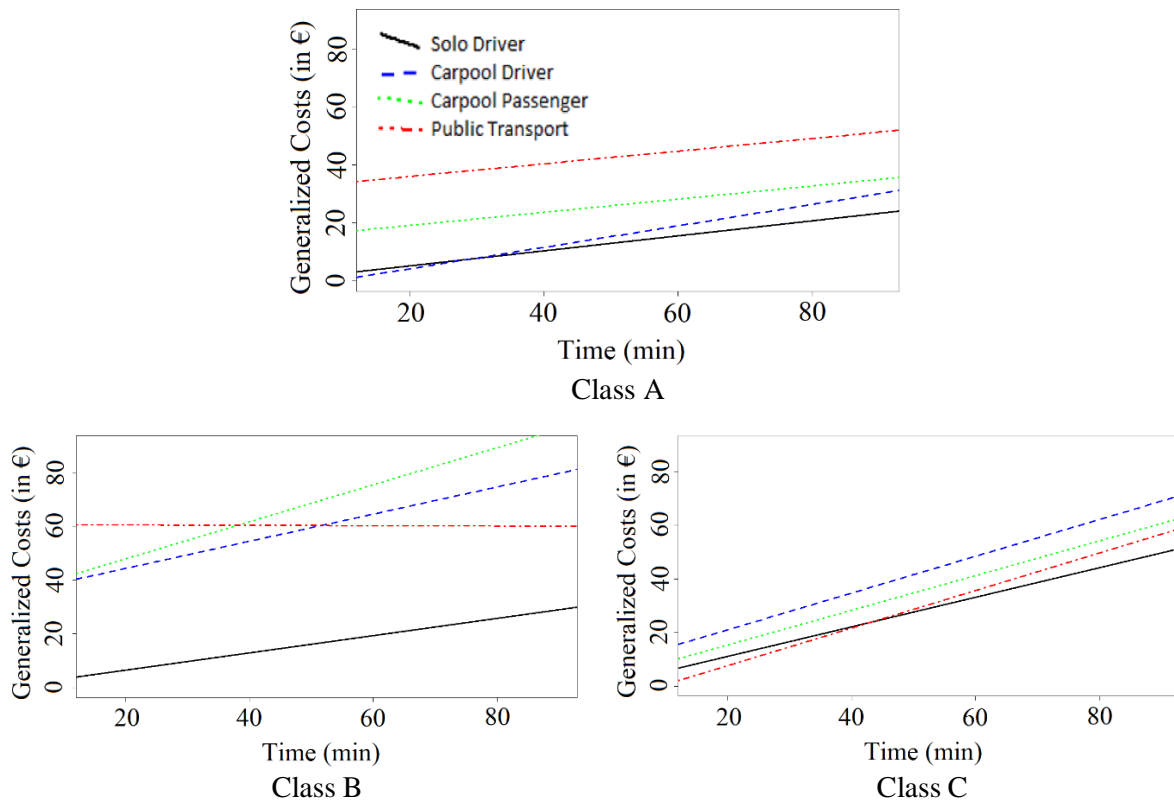
11 Mode preferences are compared between classes taking into account VoTTs and ASCs. For instance  
12 Class C has higher VoTT than other classes, but it is compensated by much lower ASC. On the contrary,  
13 Class A has low VoTT but high ASC. Moreover, in class B Public Transport ASC is so high that even  
14 if the VoTT estimate is not significant, the cost of this alternative will always be valued much higher

than the Solo Driver one. This is illustrated with the Table 5 below which displays generalized costs for each class of the LCL model for a 40 minutes trip (average trip duration in the sample, see Table 2).

**Table 5** : Generalized costs for a 40-minute trip in each mode and class in LCL

	Class A	Class B	Class C
Solo Driver	10€	13€	22€
Carpool Driver	11€	54 €	35€
Carpool Passenger	24€	62€	28€
Public Transport	40€	60 €	22€

Figure 3 shows a comparison of these generalized costs for the four modes in each class across the trip duration. Class A has overall a lower generalized cost for Solo Driver than other classes. This class values equally lower both Solo Driver and Carpool Driver, and higher Carpool Passenger and much higher Public Transport. Class B values all the modes other than Solo Driver much higher than this one. Finally, Class C presents very similar generalized costs for the four modes with a slightly higher value for Carpool Driver.



Notes: We take the values at the sample mean i.e. the representative individual<sup>14</sup> making the representative trip to compute sample average values.

**Figure 3:** Generalized Costs of a trip for the representative individual depending on mode and travel time

<sup>14</sup> The representative individual is defined with the mean values for each individual characteristic displayed in Table 2

## 6. DISCUSSION

First the values of travel time are discussed, second the preferences stated by the individuals are analyzed. Finally, we derive some policy implications.

### *Values of travel time*

An important result is the stable ranking between modal alternatives through the models. Table 6 below illustrate this ranking through relative values, 100 being the value of time in Solo Driver for each model.

**Table 6:** Relative Values of Time with Solo Driver as Reference

Attribute	Alternative	MNL	MXL1 (No Corr)	MXL2 (Corr)
TT	Solo Driver	100 (22.8€/h)	100 (20.1€/h*)	100 (25.3€/h*)
	Carpool Driver	135	139	153
	Carpool Passenger	120	120	141
	Public Transport	141	161	167

*Notes: For each model, 100 represent the value of 1 hour spent in the Solo Driver mode*

*\* Values for MXL are the median values of the estimated lognormal distribution*

In the MNL and MXL models travel time by the four modes are valued from the lowest to the highest as follows: Solo Driver, Carpool Passenger, Carpool Driver and Public Transport. These results suggest time in Carpool Driver is valued around 40% higher than solo driving, Carpool Passenger around 20% higher and Public Transport around 60% higher, based on MXL1 results.

As respondents are currently solo drivers, there is no surprise in finding Solo Driver VoTT as the lowest. An interesting result in this ranking is that the Carpool Driver travel time is valued higher than Carpool Passenger, even though our respondents are current drivers. This result shows that the longer the travel, the more the Carpool Passenger alternative is likely to be chosen compared to the Carpool Driver one. This could be explained by several facts: driving can be stressful, the time spent as a passenger can be used in a different and more pleasant way than the time spent as a driver (reading or consulting one's smartphone for instance).

Values of time found in this survey are higher than what [Wardman et al. \(2016\)](#) and [Shires & De Jong \(2009\)](#) found for commuting by car in France, respectively 11.8€<sub>2019</sub>/h and 15.4€<sub>2019</sub>/h. Several reasons may explain this. First, our sample is composed only of currently solo drivers, who may have higher incomes than the whole population and hence higher values of time. Another explanation could be that the values we find can be considered from a willingness to accept (WTA) perspective since the exercises challenge what solo drivers are willing to accept to switch to another mode (see also [Monchambert, 2020](#)). In the VoTT field, [De Borger and Forsgerau \(2008\)](#) found an important gap between WTP and WTA with a 1 to 4 factor.

The schedule late delay is valued lower than schedule early delay. This result is unexpected and opposite to what is found in the literature (de Palma & Fontan, 2000). It could be explained because respondents may have misunderstood schedule delay. They could have only observed that their departure time was later than usual and hence thought their total travel time was lower, thinking all the alternatives were arriving on time. We can also assume respondents may have a lot of flexibility, no time constraints they cannot override. However, the scheduled early value is found around 40% of the Solo Driver VoTT. This result is consistent with what was found in de Palma & Fontan (2000) in Paris, around 35%.

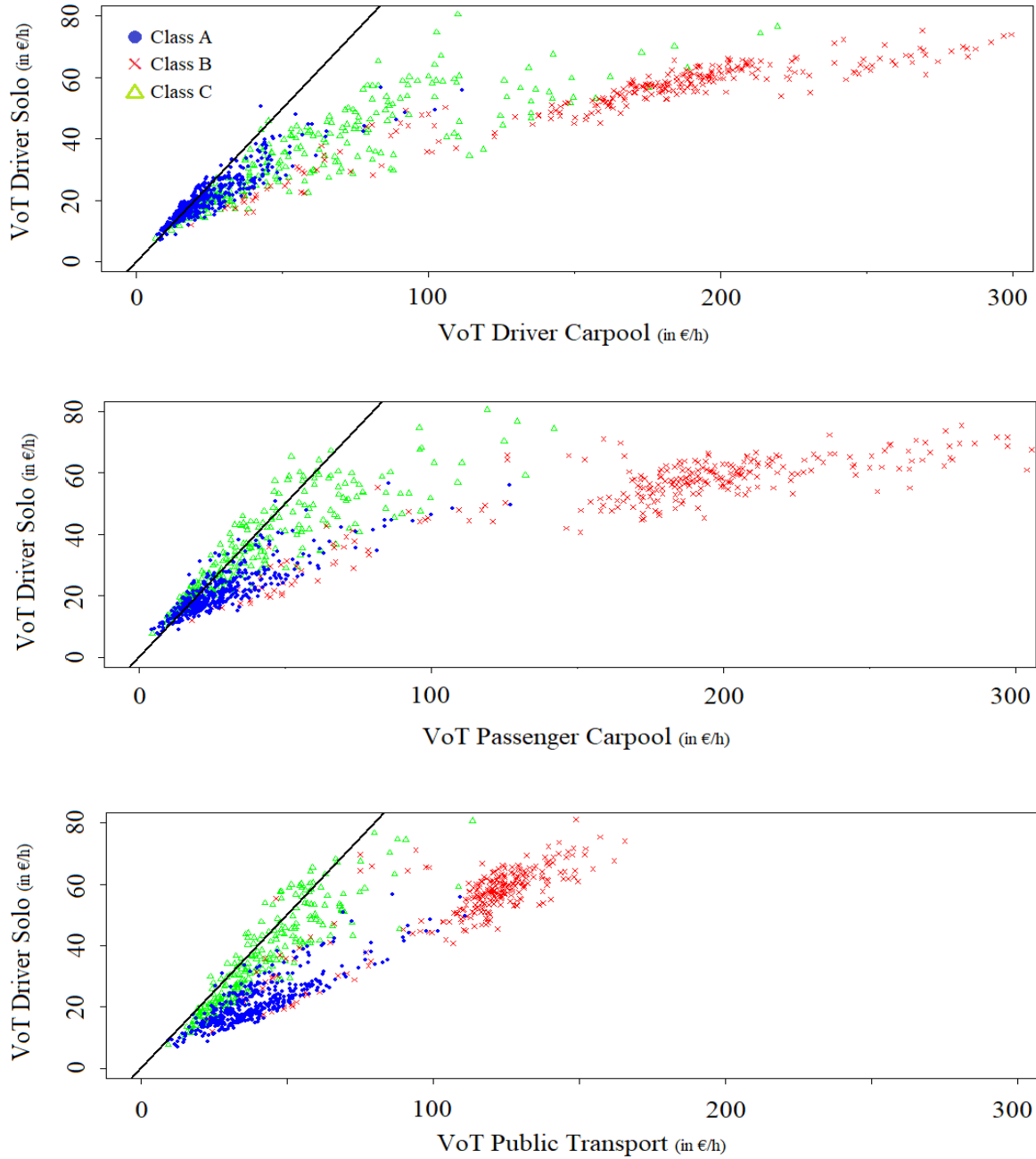
#### *Other perspectives on the heterogeneity of preferences*

Figure 4 below combines results from MXL2 and LCL models. Each individual is represented by a point showing its VoTT, estimated with the MXL2 model. Each point is characterized by the latent class to which the individual is most likely to belong in LCL. A black line of slope 1 representing points with equal VoTTs is added.

It can be observed that these points are organized in an increasing way. This means that the larger the VoTT is for the Solo Driver mode, the larger it is for the other modes as well. One can also see that the points associated with class C are distributed in a rather heterogeneous way, some with values of time among the lowest and others among the highest. Points associated with the two other classes are more homogeneous with lower values for class A and higher for class B.

Furthermore, notice that some points are clearly distinguishable from the others on the right part of the plots. They are associated with class B and far below the black line. This means these individuals therefore tend to value very high every other mode and value proportionally lower the Solo Driver. This result is consistent with what was found in the MXL correlation estimates. Individuals associated with Class C are in the upper part of scatterplots in the graphs which compare Solo Driver and passenger modes VoTT. This means these individuals have the lowest VoTT for passenger modes proportionally to their Solo Driver VoTT. Similarly, the points associated with class A can be found in the upper part of the scatterplot on graph comparing Solo Driver VoTT and Carpool Driver VoTT and hence they value the Carpool Driver proportionally lower.





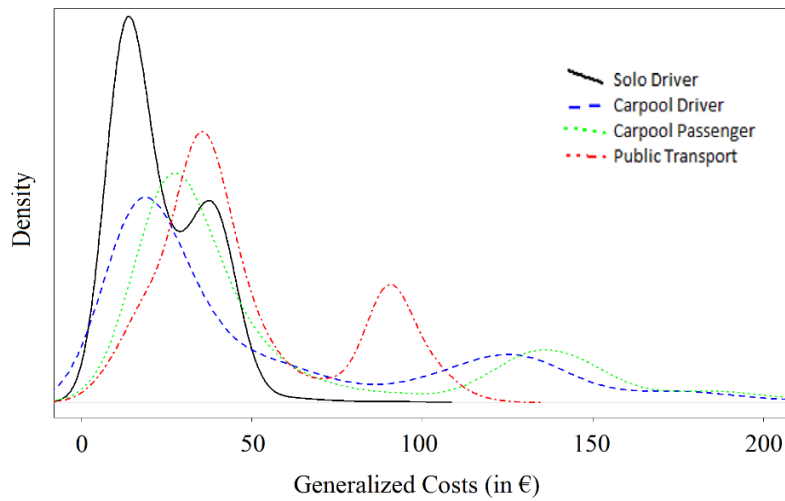
Notes: The black lines represent the points with equal VOTTs in both modes ( $y=x$ )

**Figure 4:** Distribution of individual VoTTs found in MXL2 and their associated class in LCL

Another look at the heterogeneity of preferences can be given through the generalized costs for a 40-minute trip. Figure 5 below shows the densities of the individual values of these cost functions for each mode, obtained from the MXL2.

Opposite to the consideration of only the VOTTs and due to the inclusion of alternative specific constants in the generalized cost, Carpool Driver is in general preferred to Carpool Passenger for an average trip duration. The least preferred mode is Public Transport. Moreover, some individuals have very high costs for Public Transport, where a peak is observed shortly before a 100€-generalized cost.

Overall, this graph highlights the heterogeneity of behaviors shown through the various estimations of MXL and LCL.



Notes: We take the values at the sample mean i.e. the representative individual making the representative 40-minute trip to compute sample average values.

**Figure 5:** Individual generalized costs densities in MXL2 for a 40-minute trip

#### *Stated choices and attitudes to carpool*

Thanks to the LCL model, individual stated choices can be related to the attitude statements. The first type of behavior, represented by class B, is a class that is characterized by individuals who are satisfied with their current mode choice and find hard to change that. This profile is consistent with individuals who are not very open to change and are therefore very averse to alternative modes, as shown by the high level of generalized costs of these alternatives (cf. Figure 3 and Table 5). On the contrary, class C is unsatisfied with their mode choices and could easily change. Once again, it is consistent to find that this class consider favorably all the alternatives to solo driving. Finally, class A is an intermediary of the two previous classes but is more concerned about the opinion of others. According to their choices, this class is open to the possibility of carpooling, while remaining a driver.

#### *Policy implications*

These results suggest that attitudes would be better predictors of behavior than socio-demographics.

A large part of our solo driver sample (42%) is associated to the behavior represented by class A in LCL, which could accept to switch to Carpool Driver, with a generalized cost very close from the Solo Driver one in this class. A slight incentive (around 1€ according to Table 5) should be enough to make them change from solo driving to carpool driving if end-to-end travel times are equal.

If one wants to promote carpooling to reduce car traffic, some drivers will have to switch to passengers. Individuals most likely to switch to passenger alternatives are those associated with class C, which represent 32% of our sample. However, generalized costs in this class are lower for Public Transport

than for Carpool Passenger. As a result, Public Transport is likely to be the preferred shift mode of solo drivers in class C in the case that the introduction of a HOV lane increases the generalized cost of Solo Driver. Having more former solo drivers in public transport would indeed decrease the share of solo driving but this would also make more difficult the setting-up of carpool parties. There is a risk of scarcity of carpool passengers, who are the limiting resource in carpool matching. Specific incentives should be designed to ease the recruitment of carpool passengers.

Finally, there are some people for whom it will be complicated, if not impossible, to change their minds. Fortunately, these people who are resistant to change represent only 28% of our sample.

## **7. CONCLUSION**

This paper has estimated values of travel time of four modes (Solo Driver, Carpool Driver, Carpool Passenger and Public Transport) for commuting trips. A stated choice survey conducted on a 931-respondent sample allowed us to understand modal choices through two different types of models allowing for heterogeneous tastes: mixed multinomial and latent class logits.

The originality of this paper is the focus on carpool specific values of time for daily trips, both as a driver and as a passenger. A comparison of these values is also provided with VoTT by more classic modes found in the literature: solo driving and public transport. It gives us a ranking of mode-specific values of time for currently solo-driving commuters, which is from the lowest to the highest: Solo Driver, Carpool Passenger (around 20% higher than Solo Driver), Carpool Driver (around 40% higher) and Public Transport (around 60% higher).

Individuals also react heterogeneously in their mode choice behavior. The latent-class analysis reveals these heterogeneities are explained better by the attitude statements than by socio-economic variables. Besides, it shows that finding carpool drivers seems easier than finding carpool passengers due to the competition from public transport for individuals who agree to become passengers. Incentives will therefore have to be adapted to the population to convince car commuters to switch to carpooling, especially as a passenger, which should be the scarce resource.

Finally, we know carpool organization and individual variables may impact carpool choices. This raises the question of how impactful matching between individuals can be on the decision to carpool or not. Besides, the different stages that compose end-to-end travel time can be valued differently, such as access to carpool meeting or waiting times. These effects on commuting mode choice need to be explored through further research.

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- 13

## APPENDICES

### Appendix A: An example of choice screen for a driver respondent with a 8:30 preferred arrival time

Mode	Driver Alone	Driver in a Carpool	Passenger in a Carpool	Public Transport
Trip Characteristics	<p>Start : <b>7:20</b></p> <p> Drive Alone: Between <b>30</b> and <b>40 min</b></p> <p>Arrival: Between <b>7:50</b> and <b>8:00</b></p>	<p>Start : <b>7:30</b></p> <p>Join the station: no detour Wait:  5 min</p> <p> Carpool : Between <b>25</b> and <b>40 min</b></p> <p>Join your destination:  5 min walk</p> <p>Arrival : Between <b>8:15</b> and <b>8:30</b></p>	<p>Start : <b>7:35</b></p> <p>Join the station:  5 min walk Wait:  5 min</p> <p> Carpool : Between <b>30</b> and <b>40 min</b></p> <p>Join your destination:  5 min walk</p> <p>Arrival : Between <b>8:20</b> and <b>8:30</b></p>	<p>Start : <b>7:30</b></p> <p>Join the station:  10 min by car Wait:  5 min</p> <p> Public Transport: Between <b>25</b> and <b>40 min</b></p> <p>Join your destination:  5 min walk</p> <p>Arrival : Between <b>8:15</b> and <b>8:30</b></p>
Monetary aspects	You <b>pay</b> your usual transportation costs	<p>You <b>pay</b> your usual transportation costs</p> <p>Carpooling makes you earn <b>1€</b></p>	<p>You <b>save</b> on your usual transportation costs</p> <p>Carpooling costs you <b>1€</b></p>	<p>You <b>save</b> on your usual transportation costs</p> <p>Public Transport costs you <b>0,80€</b></p>
Carpooler's profile		<p>Your passenger:  45 years old, Hitchhiker</p>	<p>Your driver:  25 years old, Referenced on the carpool platform</p>	
Which mode do you choose ?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

1 **Appendix B:** Results with Individual Parameters & Carpool Organization Controls

Attribute	Alternative	MNL	MXL1 (No Corr)	MXL2 (Corr)	Class A	LCL Class B	Class C
Constants	Carpool Driver	-0.6594***	-0.9034*	-0.2655	0.4636**	-3.6684***	-0.7033**
	Carpool Passenger	-1.0646***	-1.4399**	-0.6139	-1.0196**	-3.1775*	0.3062
	Public Transport	-1.2749***	-1.5419***	-1.0259	-3.4962***	-6.6848***	0.6728**
Time variables							
Total travel time	Solo Driver	0.3806***	-1.0922***	-0.8645***	0.2581***	0.3223***	0.5538***
	Carpool Driver	0.5126***	-0.7636***	-0.4354*	0.3699***	0.5046***	0.6874***
	Carpool Passenger	0.4564***	-0.9138***	-0.5192*	0.2264***	0.6865*	0.6476***
	Public Transport	0.5347***	-0.6193***	-0.3472	0.2187*	-0.0072	0.7023***
Schedule late	Solo Driver	0.1237***	0.0812***	0.0824***	-0.0394	-0.0533*	0.0595**
Schedule early	Solo Driver	0.1568***	0.1422***	0.1637***	0.3172***	0.1310***	0.1593***
Cost	All	-0.0861***	-0.1481***	-0.1350***		-0.1097***	
Standard deviations (in MXLs)							
sd Constants	Carpool Driver		-1.2882***	-0.4414*			
	Carpool Passenger		-1.1924***	-0.9266***			
	Public Transport		1.6304***	-1.4467***			
sd Travel time	Solo Driver		-0.3438***	-0.8069***			
	Carpool Driver		-0.3017*	0.4767***			
	Carpool Passenger		-0.3196***	0.3900***			
	Public Transport		-0.2675***	0.0558			
Correlation estimates (in MXL2)							
Between modes	Solo Driver / Carpool Driver			-1.0892***			
	Solo Driver / Carpool Passenger			-1.0451***			
	Solo Driver / Public Transport			-0.7192***			
	Carpool Driver / Carpool Passenger			0.4316***			
	Carpool Driver / Public Transport			0.1259***			
	Carpool Passenger / Public Transport			0.4102***			
Latent Class Allocation Variables							
Average Latent Class Allocation Probability					0.41	0.28	0.32
S1 (“car traffic major source”)					0	-0.1055	0.1165
S2 (“satisfied with my choices”)					0	0.3205 ***	-0.3498***
S3 (“could change easily”)					0	-0.4941***	0.2437**
S4 (“opinion matter”)					0	-0.1899*	-0.1622*
S5 (“personally responsible”)					0	-0.0541	-0.0544
Gender (1 = male)	Carpool Driver	-0,193**	-0,335*	-0,16		0,008	
	Carpool Passenger	-0,274**	-0,371*	-0,23		0,005	
	Public Transport	-0,185 *	-0,379 *	-0,265		0,164	
Age (1 = 46yo or more)	Carpool Driver	-0,415***	-0,672***	-0,413**		-0,247*	
	Pass Cp	-0,43***	-0,591***	-0,368 *		-0,143	
	Pub T	0,01	-0,098	0,127		0,39**	
Income	Driv Cp	0,148***	0,195*	0,169 *		0,085 *	
	Pass Cp	0,041	0,013	-0,044		-0,113 *	
	Pub T	0,119*	0,151	0,009		-0,115	
Male Passenger	Driv Cp	-0,242***	-0,365***	-0,35***		-0,317***	
Age Passenger	Driv Cp	0,032	0,13	0,108		0,08	
Male Driver	Pass Cp	-0,162	-0,274 *	-0,292*		-0,219*	
Age Driver	Pass Cp	0,037	0,072	0,083		0,039	



Carpool Organization				
Relative Driv Cp	0 (ref)	0 (ref)	0 (ref)	0 (ref)
Planif Platform	-0,141	-0,24 ‘	-0,176	-0,204
Spont Platform	0,15	0,224	0,181	0,139
Hitchhiker	-0,12	-0,211	-0,256	-0,245 ‘
Relative Pass Cp	0 (ref)	0 (ref)	0 (ref)	0 (ref)
Planif Platform	-0,14	-0,263	-0,279	-0,277 ‘
Spont Platform	0,103	0,121	0,017	0,025
Hitchhiker	-0,37*	-0,542*	-0,566 ‘	-0,453**
Carpool organization controls	Yes	Yes	Yes	Yes
Carpool Driver/Passenger controls	Yes	Yes	Yes	Yes
Individual characteristics controls	Yes	Yes	Yes	Yes
Nb of individuals	931	931	931	931
Nb of observations	5586	5586	5586	5586
Nb of parameters	29	36	42	55
LL(final)	-5931.2	-5263.9	-5125.7	-5027.3
Adj.Rho-square (0)	0.2303	0.3156	0.3327	0.3437
AIC	11920.4	10599.7	10335.3	10164.7
BIC	12112.6	10838.3	10613.7	10529.2

*P-values: 1 ( ) 0.1 (‘) 0.05 (\*) 0.01 (\*\*) 0.001 (\*\*\*) 0.*

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### Appendix C: Non-traders & Fast answerers in the sample

Characteristics	Answered in < 6 sec	Answered in > 6 sec	Total
Never Choose Solo Driver	60	625	685
Choose Solo Driver at least once	220	931	1151
Total	280	1556	1836

4

1 **Appendix D:** Trip attributes and levels in stated choice design

Attributes	Alternatives	Levels
<b>Time variables</b>		
Schedule early/late	Solo Driver	0, 30, 60 minutes (earlier or later)
Access time	Passenger modes*	5 minutes walking (ref), 10 minutes by car, 20 minutes by car
Detour time	Carpool Driver	0, 5, 10 minutes
Waiting time	Passenger modes and Driver in Spontaneous Carpool	0, 5, 10 minutes
In vehicle travel time	All	Solo Driver: (0.8, 1.1, 1.5) * usual_tt Other modes: (0.6, 0.9, 1.2) *usual_tt
Travel time variability	All	(0.1, 0.3, 0.5) * TT
Egress time	Passenger modes	Carpool passenger: 5 min walking (ref), 10/20 min by Public Transport Public transport: 5 min walking
<b>Cost</b> (in €)	Carpool modes* and Public Transport	Carpool Driver: receives (0, 0.02, 0.05, 0.1) * usual_tt Carpool Passenger: pays (0, 0.02, 0.05, 0.1) * usual_tt Public transport: pays 0.8
<b>Carpooler profile</b>		
Carpooler matching	Carpool modes	Planned, Spontaneous
Carpooler Gender		Male, Female (not presented if relative)
Carpooler Age		25, 45, 65 years old (not presented if relative)

*Notes: Passenger modes: Carpool Passenger and Public Transport. Carpool modes: Carpool Driver and Carpool Passenger. "usual\_tt" is the usual travel time the respondent reports in the survey*