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## WORKING PAPERS DU LAET

NUMÉRO  
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*Keywords: Carpool; Subsidy; Short-distance; Two-way fixed effect*



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# Does subsidy increase carpooling usage? The case of short-distance carpooling in France\*

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March 26, 2024

## Abstract

Many initiatives have been introduced worldwide by governments and industries to promote carpooling usage. In France, some local authorities have introduced carpooling subsidy policies since 2019 to encourage traveling by carpooling. We estimate the effect of local carpooling subsidies on the usage of short-distance carpooling organized by platforms using a difference-in-differences design that exploits variation across French “Communautés de Communes” (i.e. local authorities) in both the amount of subsidy and the timing of subsidy policy start. We find that the implementation of the carpooling subsidy increases the number of monthly short-distance carpool trips organized by platforms by around 5.5 trips per 1,000 inhabitants in the local authority area, and that this effect increases over time. Moreover, a 1-euro increase in carpooling subsidy improves the number of monthly carpool trips organized by platforms per 1,000 inhabitants by 3.9 trips and such an effect also increases with time. These average effects mask considerable heterogeneity, with subsidy increasing carpooling usage more in larger and higher-density local authority areas and the effect being negligible for local authority areas with the smallest size and density. Our results also suggest that carpooling subsidy effects do not differ with local authority area median income.

**Keywords:** carpool; subsidy; short-distance; two-way fixed effect

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## 1. Introduction

The intensification of global warming issues makes it vital to control greenhouse gas emissions (GHG) and the negative impact of transportation. In Europe, transportation sector contributes a quarter of GHG emissions and half of it comes from passenger cars (Santarromana et al., 2020). Also, traffic congestion is a serious problem in large cities due to large volumes of cars on roads during peak hours. According to INRIX (2022), drivers in Paris, Lyon and Marseille - France's three most congested metropolitan areas - lost on average 138, 92 and 83 hours in road congestion in 2022. However, traveling alone in a car is still the norm throughout France, with the average car occupancy rate being 1.43 in 2019 for local mobility (Brahmi et al., 2022). Traveling alone increases road pressure and is a great waste of resources. With the development of network technology, carpooling platforms as a new mode of transportation sharing has emerged. Carpooling platforms make it possible to have more matchings between empty seats and passengers, and use a large unused transport capacity to increase car occupancy rate (Shaheen, 2016). A large adoption rate of carpooling platforms is a potential solution for transport congestion and resource-saving.

To encourage more usage of carpooling, governments and carpooling platforms worldwide implement various incentives for carpoolers. For example, DiDi Chuxing, one of the earliest and largest carpooling platforms in China, has spent a large portion of its revenue on carpooling subsidies. In 2021, 4.7% and 10.9% of its total income were used to subsidize carpooling drivers and passengers, respectively (Wu et al., 2023). In Belgium, the government has constructed carpool parkings to enhance parking amenities and serve as incentives for carpooling<sup>4</sup>. In the US, Canada, Europe, Australia, China and other parts of the world, provision of dedicated lanes such as high occupancy vehicle (HOV) lanes is frequently employed (Cohen, 2022). The French government authorized subsidies and HOV lanes for carpooling users in 2019 with the LOM ("Loi d'Orientation des Mobilités") law.

Most of related research on carpooling subsidies effects remains at the theoretical level of analysis (Yu et al., 2019; Tafreshian & Masoud, 2022; Monchambert, 2023; Wu et al., 2023), or

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<sup>4</sup> <https://newmobility.news/2023/09/25/wallonia-gets-11-extra-carpool-car-parks/>. (Accessed 2024-3-2)

uses stated preferences surveys (Monchambert, 2020; Bulteau et al., 2021; Le Goff et al., 2022, 2023, 2024), but there is little empirical evidence from revealed preferences data. This study contributes to this new body of revealed preference empirical evidences on subsidies effects of carpooling. Thus, we address the following research questions: what is the effect of implementing a carpooling subsidy policy on its usage? Does the effect vary with the subsidy amount? and how do these effects change over time? We especially test for heterogeneity of subsidy effects across different local authority areas depending on population, density, and income. By addressing these questions, we aim to identify the factors affecting carpooling subsidy effectiveness.

We contribute to the literature by making a comprehensive investigation of the subsidy effects on carpooling usage based on a unique database from 1 123 local authority areas (which we refer to as “cities groups” for the sake of ease), covering a period from 2019 to 2023. By employing a two-way fixed effect model method, we aim to establish a causal relationship between local carpooling incentives and carpooling usage. We also conduct a time trend analysis to examine the subsidy changes over time. Finally, we make a detailed heterogeneity analysis for different sizes, densities and incomes of cities groups.

We quantify the carpooling subsidy effects and find that local subsidies can significantly improve carpooling usage. In particular, we find that the implementation of the carpooling subsidy increases the number of monthly carpool trips organized by platforms by around 5.5 trips per 1,000 people in the cities group and such an effect becomes more significant in promoting carpooling usage over time, but its growth diminishes over time. Moreover, a 1-euro increase in carpooling subsidy increases the number of monthly carpool trips organized by platforms per 1,000 people by 3.9 trips and it also increases with time. These average effects mask considerable heterogeneity, with subsidy increasing carpooling usage more in larger and higher-density cities groups and the effect being negligible for cities groups with the smallest size and density. Our results also suggest that carpooling subsidy effects do not differ with median disposable income across cities groups.

The remainder of this paper is as follows. Section 2 is a review of related literature. Section 3 provides background information on the French carpooling market. Section 4 presents data

sources and variables. Section 5 specifies the econometric model. Estimation results are presented in section 6, including parallel trend test, baseline regression, and time effect analysis. Section 7 examines the heterogeneous subsidy effects across different types of cities groups. Finally, Section 8 gives concluding remarks and provides some policy implications.

## 2. Related literature

This study is mainly relevant to two research streamlines, carpooling platforms and the efficiency of policies in carpooling usage.

### 2.1. Carpooling platforms

The sharing economy can enable the use of underutilized products without invoking the transfer of individual ownership, and improve resource efficiency (Heinrichs, 2013). In the transport industry, due to the advancement of information technology, people's growing awareness of environmental issues, and cost reduction needs after the 2000s economic crises, sharing platforms like BlaBlaCar are getting popular (Shaheen et al., 2017). These platforms can match and connect empty seats provided by private drivers and passengers who need rides, thus they are also two-sided platforms. One main characteristic of a two-sided platform is that more demand from one user side spurs more supply from another provider side (Rochet & Tirole, 2006). For example, the more drivers register at a carpooling platform, the more passengers join the platform because there is a larger possibility for them to match a seat. In turn, the more passengers register at the platform, the more car owners are willing to provide seats because it is more likely to find a suitable passenger (Monchambert, 2023). Noting this characteristic of carpooling platforms helps to decipher the impact of the policy on them.

There is a vast literature on analyzing why people choose to carpool. The literature identifies three major incentives for carpooling: financial gains, environmental protection, and time-savings (Delhomme & Gheorghiu, 2016). On the one hand, sharing a car with people who have the same origin and destination can save monetary costs (e.g., fuel cost, tolls, parking charges, etc) and spend enjoyable time with other people (ADEME survey, 2015; Monchambert, 2020). On the other hand, however, the inconvenience of carpooling and personal safety risks will reduce people's intention to carpool (Le Goff et al., 2022; Yu et al., 2019). Platform is a way to create

trust between drivers and passengers, and to reduce these obstacles (Le Goff et al., 2023). One of the first empirical research is by Teal (1987). Based on the US transportation survey data, it analyzes the characteristics of carpoolers and offers explanations. More recently, Prieto et al., (2017) use survey data from London, Madrid, Paris, and Tokyo, to consider the impact of socio-demographic variables on car-sharing behavior and explore individual choice. They find living in the city center, being male, and being highly educated significantly increase the probability of carpooling adoption. Brown (2020) studies trip level data of 6.3 million Lyft trips. Findings reveal that people in neighborhoods with higher density, lower income and less racial and ethnically diverse are more likely to carpool. Monchambert (2020) builds a discrete choice model to estimate the probabilities of choosing carpooling among buses, trains, and solo cars for long-distance trips in France. The author further measures socioeconomic factors such as gender, age, and income's effect on carpooling choice. There are also similar studies point out that a large proportion of carpoolers are young adults (younger than 30 years old) and those who have no cars (Sarriera et al., 2017; Spurlock et al., 2019). Many carpoolers choose to share rides because they offer lower prices compared to non-shared services. Lower price and time savings are more important than the potential social interactions during carpooling (Sarriera et al., 2017). Drawing on identity theory, Hartl et al., (2020) found the extent of an environmentalist identity can predict car drivers' willingness to carpool and offer a ride, yet it is not significant in passengers.

## 2.2. Policy effectiveness study

The slow development of the carpooling mode for short-distance journeys has attracted a substantive academic effort to understand its constraints. A rich body of research studies the effectiveness of various incentives for carpooling usage. There are policy attributes such as monetary incentives (Le Goff et al., 2024), offering reserved parking spaces for carpools (Xiao et al., 2016), and providing carpool-only lanes such as high-occupancy vehicle (HOV) and High-occupancy toll (HOT) lanes (Cohen et al., 2023; Zhong et al., 2020), and also congestion price (Konishi & Mun, 2010). For example, Xiao et al., (2016) investigate a morning commute problem with carpooling choice under parking space constraints. Compared with solo drivers, carpoolers have shorter rush hours due to the extra carpool cost. Cohen et al., (2023) run a digital field experiment by sending users notifications with different framing. They found mentioning



the HOV lane and the resulting time reduction is an effective incentive to persuade users to carpool. [Zhong et al., \(2020\)](#) analyze carpooling in morning commute. They build a bottleneck model and find that HOV lanes promote carpool and improve welfare. A larger capacity of the HOV lane is always beneficial to the system. In addition, a HOT lane can boost welfare with a modest level of toll. [Konishi & Mun \(2010\)](#) build a theoretical model to study the welfare effects of HOV and HOT lane policies. They also examine the efficiency of two pricing policies of uniform and differential congestion pricing. They find it varies depending on the parameters and road conditions.

The implementation of monetary incentives can influence usage behavior by changing people's attitudes toward carpooling ([Saxena & Gupta, 2023](#)). [Tafreshian & Masoud \(2022b\)](#) address the problem of tight time windows during the carpooling matching process. They propose a subsidy scheme to travelers and make them less sensitive to undesirable departure or arrival times. It shows the subsidy scheme would improve social welfare for a market with a low penetration rate and few flexible users. [Tafreshian & Masoud \(2022a\)](#) also find that instead of directly subsidizing travelers for carpooling, it is more beneficial to allocate subsidies to change their travel behavior. Similarly, [Wu et al. \(2023\)](#) optimize a carpooling incentive scheme to change commuters' departure patterns to alleviate traffic congestion. [Yu et al. \(2019\)](#) consider the heterogeneity of carpoolers and propose an allocation of subsidy to carpooling. They get the conclusion that the optimal subsidy for carpooling should be relied on users' demand sensitivity to the subsidy. [Monchambert \(2023\)](#) finds that profit-maximizing platforms do not subsidize efficiently the "good" side of the market, leading to very little traffic reduction. [Bulteau et al. \(2021\)](#) use logistic regression models to explore the determinants of carpooling usage as a passenger or driver. They show contextual variables (e.g., the location of residence and work) are more important for carpool drivers while individual variables (e.g., social-demographic and economic) play a major role for carpool passengers. The studies mentioned above provide mixed evidence on heterogeneous subsidy effects on carpooling usage. However, they remain at the theoretical level of analysis or use stated preference surveys, and there is little revealed preference empirical evidence. Our study fills part of this gap by using revealed preferences to study the effect of subsidies on through-platform carpooling usage.

### 3. Carpooling in France

This section gives details about the background of our study. We start with the definition of Carpooling in France, and then introduce the carpooling related policy such as the LOM law. The dataset contributed by carpooling platforms and the car sharing evidence register (RPC) make it possible to estimate carpooling subsidy effects on carpooling usage organized by platforms.

#### 3.1. Legal definition of carpooling in France

Carpooling is recognized by many names, including ride-sharing, car-sharing or lift-sharing. According to the French Transport Code, carpooling is when a non-professional driver shares a vehicle with one or more passengers for all or part of the driver's planned trip without payment, except for the sharing of costs<sup>5</sup>. Two conditions should be met: first, the journey is made by the driver's own account and not aim for seeking to transport people. Second, the driver can share only travel variable costs with the passenger and the driver does not make any profit from it. Thus, carpooling differs from ride-hailing in that ride-hailing is when a passenger requests a driver to take him/her to the destination. In addition, ride-hailing is a profit-making activity (Lazarus et al., 2021).

#### 3.2. Carpooling in the “Loi d’Orientation des Mobilités” (LOM)

In France, 70% of commuting to work is done by private car, most of which are solo car trips, and only 3% is achieved by carpooling<sup>6</sup>. Around 900,000 daily trips have been made by carpooling in 2022<sup>7</sup>. Despite its cost-effective characteristics, carpooling usage is still low in France. In December 2019, LOM law was published in France to make everyday transport easier, less costly, and cleaner<sup>8</sup>. It has given local authorities the ability to subsidize carpooling

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<sup>5</sup>This definition is defined by Article L. 3132-1 of the French Transport Code. Please see: <https://www.service-public.fr/particuliers/actualites/A15032?lang=en> (Accessed 2024-03-04).

<sup>6</sup>Source:<https://www.ecologie.gouv.fr/covoiturage-en-france-avantages-et-reglementation-en-vigueur>. (Accessed 2023-10-1)

<sup>7</sup>Source:[https://www.ecologie.gouv.fr/sites/default/files/22243\\_plan-Covoiturage\\_DP\\_V2maj.pdf](https://www.ecologie.gouv.fr/sites/default/files/22243_plan-Covoiturage_DP_V2maj.pdf). (Accessed 2024-03-04)

<sup>8</sup> Source: <https://www.ecologie.gouv.fr/loi-dorientation-des-mobilites>. (Accessed 2024-03-04)

trips. Local governments can support carpooling usage through economic incentives to subsidize drivers or passengers. Passengers can carpool for free or for a few euros, with a lower travel cost, and drivers receive a bonus for each person they transport.

### 3.3. Carpooling platforms

Carpooling platforms make it possible to match drivers and passengers ahead of the trip. A carpooling match is constrained in 3 dimensions: origin, destination and time of travel, which requires a high density of trip offerings to consistently find suitable matches (Wright et al., 2020). However, according to an individual mobility survey (2018-2019) carried out by SDES-INSEE, carpooling is mostly informal and without platforms. 96 % of carpooling is carried out with friends, family or colleagues. Less than 4% of carpooling journeys are made via carpooling platforms, approximately 40,000 trips per day<sup>9</sup>.

In addition, carpooling platforms are useful and essential intermediaries between local authorities and carpoolers for distributing subsidies, because local authorities have the legal powers to subsidies, but not the technical skills. Carpooling platforms can keep track of the status of carpooling usage and report trip information to local authorities. It's helpful to monitor if the trip is actually performed.

### 3.4. The car sharing evidence register (RPC)

To monitor changes in short-distance carpooling practices in France over time, the National Observatory for Daily Carpooling<sup>10</sup> has been implemented. This system aims to monitor changes in short-distance carpooling usage in France and builds a public dataset as known as the “Registre de Preuve de Covoiturage” (RPC) dataset. The RPC dataset tracks daily carpooling usage on 26 partner carpool operators<sup>11</sup>. Note that these data only pertain to trips made through the carpooling platforms. It is a digital service provided by the government to promote the spread of carpooling usage, which aims to help the public and private players in the car-sharing ecosystem to work together more effectively, and also to facilitate the implementation

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<sup>9</sup><https://observatoire.covoiturage.gouv.fr/observatoire/comprendre-covoiturage-quotidien/>. (Accessed 2023-10-1)

<sup>10</sup> Source: <https://observatoire.covoiturage.gouv.fr/>. (Accessed 2023-10-1)

<sup>11</sup> Source: <https://www.data.gouv.fr/en/organizations/registre-de-preuve-de-covoiturage/>. (Accessed 2023-10-1)

of carpooling policies. The data can be used to evaluate the impact of measures implemented by the government or companies and develop more efficient policies. Our study leverages the RPC dataset to evaluate carpooling subsidy effects. The RPC dataset contains only carpooling trips organized by a platform. It does not contain the universe of carpooling trips. The results we obtain will therefore be limited to trips organized using car-sharing platforms. Moreover, the dataset offers no information on the modal origin of carpoolers. We do not know what their choices would have been in the absence of a platform and/or subsidy: driving alone, informal carpooling, use of public transport, no trip... However, this dataset and our results remain relevant and interesting, as they allow us to identify the effect of subsidies on the attractiveness of car-sharing platforms, and to characterize the heterogeneity of the subsidy effect between different types of cities groups.

Following the implementation of local subsidies on carpooling, the carpooling industry in France has achieved rapid growth. Figure 1 shows the trend of carpooling usage on platforms in France since February 2019. In December 2019, The Mobility Orientation Law was published. Thus many local authorities, including the regions, departments, and EPCIs<sup>12</sup> started to invest in the carpooling industry. Usage of carpooling has gradually increased since the implementation of the policy. Yet since March 2020, the development of carpooling has been strongly affected by the COVID-19 epidemic. In the summer of 2021, the COVID-19 epidemic eased in France. Plus, the outbreak of war in Ukraine in February 2022 increased energy prices. These factors have led to a sustained and large increase in carpooling. Due to the lack of data, we are unable to know the total carpool usage. However, based on the impact of the events described above on people's carpooling behavior, we find that the trend of carpooling usage on the platform and total carpooling usage are similar. Therefore, the impact of the subsidy policy on carpooling platform usage can be used as a reference for the impact of the subsidy policy on total carpooling usage.

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<sup>12</sup> An ECPI (Établissement Public de Coopération Intercommunale) is a French administrative structure grouping together several cities in order to exercise some of their powers jointly.

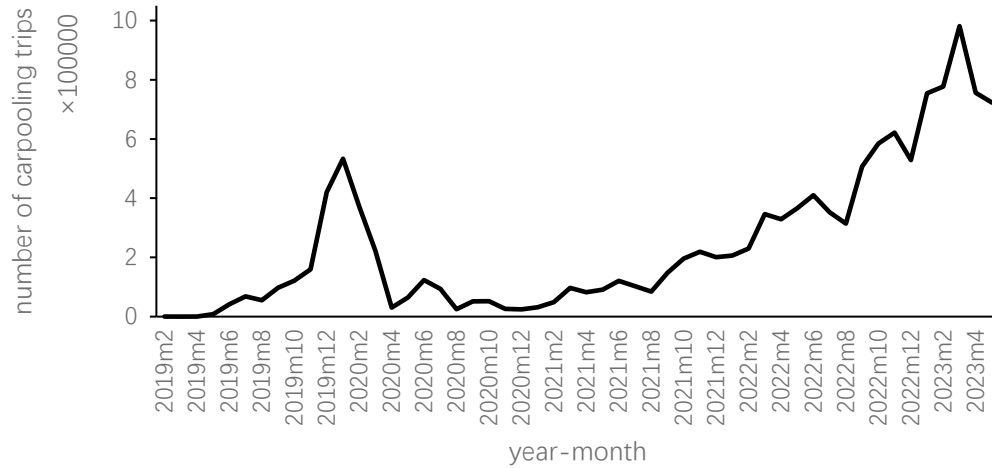


Figure 1. The trend of Carpool Trips in France

Notes: This figure shows the monthly carpool trips in France between 2019 and 2023. The data source is from the RPC dataset. We calculate the sum of carpooling usage on carpooling platforms by year-month.

## 4. Data

In this study, three different categories of data are used: first, data on carpooling trip records from the Registre de Preuve de Covoiturage (RPC) of the French market; second, data related to local governments' carpooling subsidy information; and third, data on social-economic characteristics for cities groups. This section describes our data and measures. Summary statistics of the main variables are shown in

Table 1.

### 4.1. Unit of observation

The unit of observation in our analysis is defined by cities group (EPCI) / year-month. We have defined the subject of study as EPCI for two reasons. First, the smallest unit to have local incentive policies is EPCI. Local incentives can be implemented at four levels. The most basic of these is the EPCI level, followed by the AOM level, department level, and region level<sup>13</sup>. For example, four regions have local incentives, including Normandie, Île-de-France, Occitanie, and Pays de la Loire. Each region, AOM, and department includes many EPCIs. We unify the

<sup>13</sup> Source: <https://www.ecologie.gouv.fr/covoiturage>. (Accessed 2023-10-1)

information on all incentive policies at the EPCI level. Second, each EPCI has a corresponding ID, which is convenient to trace.

#### 4.2. Carpooling trip records

Our data on carpooling trip records is from Registre de Preuve de Covoiturage (RPC). RPC dataset is collaboratively built by French mobility organizing authorities and carpooling operators. It contains detailed carpool information in France from 2019 to 2023. As a free public digital service, it aims to facilitate and secure the implementation of incentives for short-distance carpooling (Cerema, 2022). As of September 2023, a total of 23 carpooling operators are contributing trip records to PRC data<sup>14</sup>. It covers a wide range of French carpooling platforms, including BlaBlaCar, the most popular carpooling operator with a large user base<sup>15</sup>. It records monthly carpooling trips since February 2019, including the location and time information of trip start and end points, and also the estimated distance and duration of each trip. To adjust carpooling trip volumes, the present work has used the population data in 2020 from Institut National de la Statistique et des Etudes Economiques (INSEE)<sup>16</sup>. We also supplement these data with information on the local governments carpooling incentives in France.

Government incentives are usually different for long-distance and short-distance carpooling, and to facilitate analysis, we focus on short-distance trips ( $\leq 80$ km) and drop long-distance trips<sup>17</sup>. Each trip record corresponds to a carpool passenger/driver pairing. We plot the time trend of the number of carpooling trips per 1,000 inhabitants in nine cities groups. It is the number of monthly trips divided by the population size of the cities group. These cities groups are randomly chosen to visually show how the implementation of subsidy policy would affect the carpooling ridership per inhabitant. As shown in Figure 2, most cities have seen a significant increase in carpooling usage after the subsidy was implemented. It should be noted that some

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<sup>14</sup> Source: <https://covoiturage.beta.gouv.fr/operateurs/>. (Accessed 2023-10-1)

<sup>15</sup> At the end of 2021, BlaBlaCar's French market had 20 million users, and 60% of the population between 18 and 35 years old is registered with it. Source: [https://blog.blablacar.com/newsroom/news-list/blablacar-reaches-100-million-members-for-its-15th-anniversary#:~:text=BlaBlaCar%20connects%20members%20looking%20to,18%2D35%20years%20old%20population](https://blog.blablacar.com/newsroom/news-list/blablacar-reaches-100-million-members-for-its-15th-anniversary#:~:text=BlaBlaCar%20connects%20members%20looking%20to,18%2D35%20years%20old%20population.). (Accessed 2023-10-1)

<sup>16</sup> Source: [https://statistiques-locales.insee.fr/#c=indicateur&i=pop\\_legales.popmun&s=2020&t=A01&view=map4](https://statistiques-locales.insee.fr/#c=indicateur&i=pop_legales.popmun&s=2020&t=A01&view=map4). (Accessed 2023-10-1)

<sup>17</sup> For the threshold of long and short trips, please see: <https://www.ecologie.gouv.fr/covoiturage-en-france-avantages-et-reglementation-en-vigueur>. (Accessed 2023-10-1)

carpooling usage may not have been recorded in our database before the implementation of the policy. It is possible that, after the implementation of the subsidy policy, these private carpoolers use the carpooling platform to obtain the subsidy, and it is only at this point that these records are kept in the database. The failure to take this fact into account means that our results cannot be generalised to all carpooling journeys, but only to journeys organised by a carpooling platform.

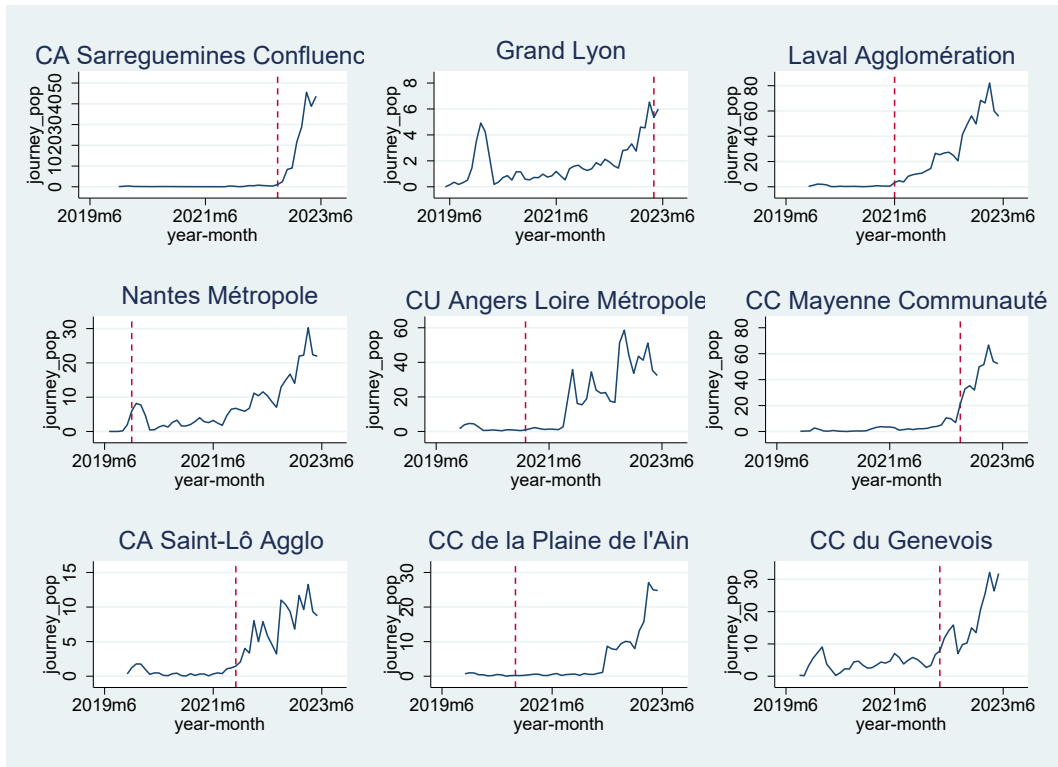


Figure 2. Carpooling in different cities groups

Notes: The vertical axis of `journey_pop` measures the number of carpooling trips per 1000 inhabitants in every cities group. Data on population is from the Recensement de la Population (RP) 2020. The horizontal axis is year-month, and the dotted line perpendicular to the horizontal axis represents the time of carpooling subsidy implementation.

### 4.3. Subsidy information

We manually obtained information on government incentives from the Local government websites and news coverage, as shown in Figure 3 start dates of carpooling subsidies and Figure 4 the map of carpooling incentives in France. In the end, we find that a total of 400 cities groups received local policy incentives among 1123 cities groups. The start and end times of the policy are different, and they are distributed at different times from 2019 to 2023.

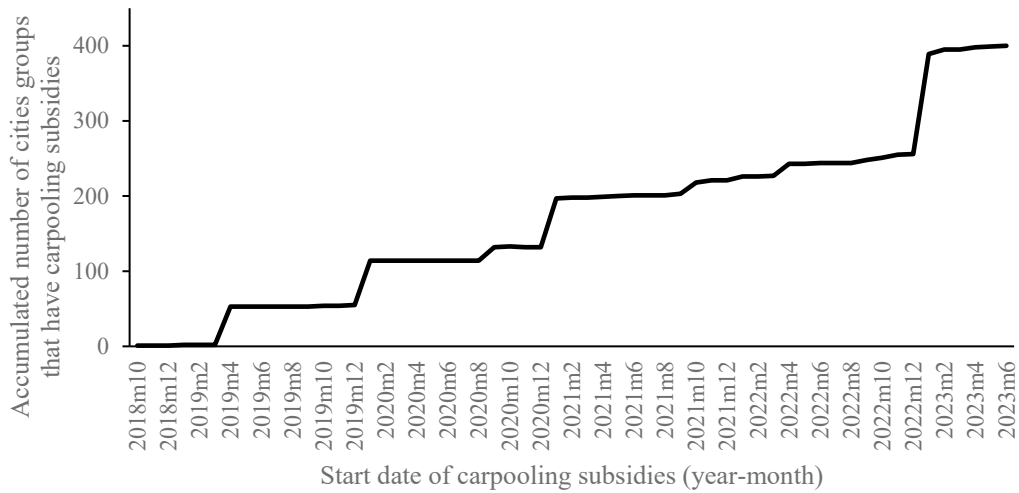


Figure 3. Start dates of carpooling subsidies

Notes: x-axis is the date of implementing carpooling subsidy in cities groups. y-axis is the accumulated number of cities groups that have carpooling subsidies. There are 400 cities groups having carpooling subsidies until June of 2023.

To approximate the subsidy allowed by a local authority, we compute the subsidy amount given for a journey by taking the average carpooling distance of the sample data as a benchmark (22km). The subsidy per trip is defined as the difference between the driver’s gain and the passenger’s cost for a carpooling trip of 22 kilometers:

$$\textit{subsidy} = \textit{driver gain} - \textit{passenger cost}$$

For example, in the cities group “CC Sarrebourg Moselle Sud”, a local subsidy policy is implemented from October 2021 onwards. The details are free carpooling for passengers and a subsidy of 2€ for drivers to transport each passenger up to 20km and 0.1€ per kilometer thereafter. In this case,

$$\textit{driver gain} = 2 + 0.1 \times 2 = 2.2\text{€}$$

$$\textit{passenger cost} = 0\text{€}$$

$$\textit{subsidy} = 2.2 - 0 = 2.2\text{€}$$

Then the subsidy is 2.2€. In the cities group “CA Agglomération du Choletais”, the carpooling passengers should pay 1.45 euros for the ride. In this case,  $\textit{subsidy} = \textit{driver gain} - 1.45$ .



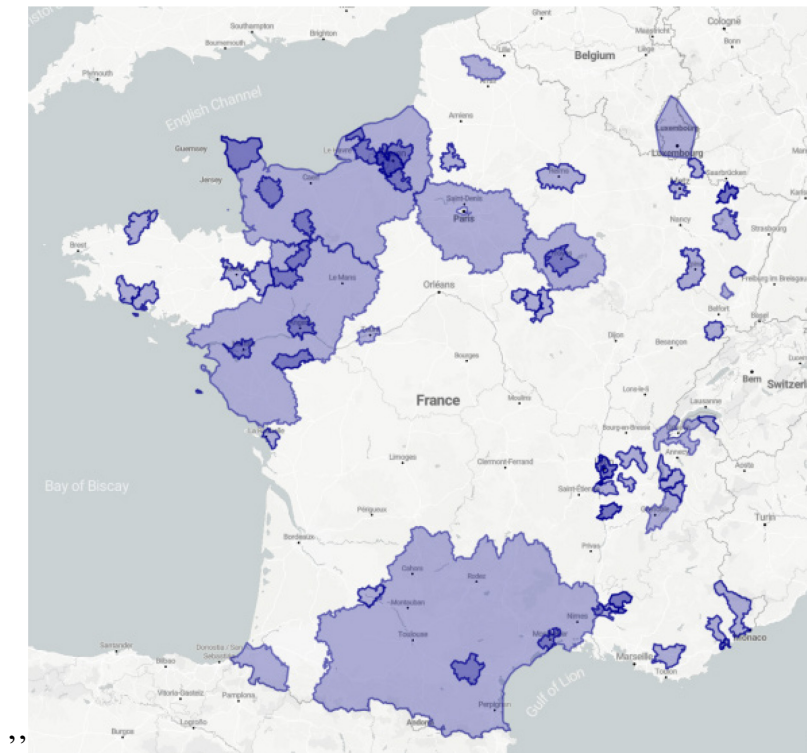


Figure 4. Map of carpooling incentives<sup>18</sup>

Notes: the map shows the spatial distribution of the cities groups that have carpooling incentives until September of 2023. Blue shading marks those areas receiving policy incentives. Overall there are four regions with carpooling incentives (Normandie, Île-de-France, Occitanie, and Pays de la Loire) with large shadings, and other small dispersed areas are different cities groups.

#### 4.4. Social-economic characteristics

We also use socioeconomic variables that are highly correlated with carpooling subsidy policy in each cities group. These potential determinants are population, median disposable income and also percentages of young people (% , <25 years), car ownership (%), and service industry (%) at the cities group level. We collect the data from the « Institut National de la Statistique et des Etudes Economiques » (2020) in France<sup>19</sup>. The reason we chose these variables is that these socioeconomic significantly influence aggregate ridership for various transportation modes (Bulteau et al., 2019). The carpooling ridership in a cities group will be closely related to the policy-making regarding carpooling in that cities group. Therefore, we hypothesize that these

<sup>18</sup> Source: [https://umap.openstreetmap.fr/fr/map/campagnes-dincitation-covoiturage\\_844182#6/46.476/5.295](https://umap.openstreetmap.fr/fr/map/campagnes-dincitation-covoiturage_844182#6/46.476/5.295) (Accessed 2023-10-1)

<sup>19</sup> Source: <https://statistiques-locales.insee.fr/#c=indicator&view=map15> (Accessed 2023-10-1)

socioeconomic variables are predictors of when and whether the carpooling incentives would be implemented in cities groups. We test these hypotheses in Appendix B.

#### 4.5. Data description

Table 1 is the summary statistics of our data. Panel A shows the statistical results of each trip record, in which the average distance of carpooling trips is 22km and the average duration is 26 minutes. Aggregating by year-month with each cities group, we obtain the statistical results of panel B. Average monthly total duration of carpooling trips in cities group is 6,175 minutes, total distance is 5,770km, and the number of carpooling trips is 228. Panel C is the subsidy statistics. In all the cities groups where carpooling incentives have been implemented, the mean driver's gain across cities groups with subsidies is 2.17€, the mean passengers' cost is 0.49€, the average subsidy per 22-km carpooling trip across cities groups is 1.68€.

Table 1. Summary statistics

Variable	Mean	Median	Min	Max	Std. Dev
<b>Panel A: Carpool trips summary statistics</b>					
Distance in meter	21,986.55	18,186.00	0	80,000	16,479.14
Duration in minute	26.45	24.00	0	1429	16.83
Number of observations	12,800,785				
<b>Panel B: Cities group statistics</b>					
Population	57,843.87	24,895.00	3920	7.09e+06	2.40e+05
Density	165.49	72.10	6.60	7,706	376.38
Share of young people (%)	27.16	27.30	17.30	39.30	3.58
Share of service industry (%)	23.98	23.50	10.80	48.50	5.07
Share of car ownership (%)	82.54	84.10	26.70	92.20	6.83
Income level (€)	22,203.19	21,710	14,690	38,480	2,326.09
Duration of monthly trips	6,174.99	834	0	2.81e+05	21,368.22
Distance of monthly trips	5.77e+06	8.76e+05	3311	2.49e+08	1.90e+07
Number of monthly trips	227.99	31.00	1	12,567	839.93
Number of observations	1123 cities groups 20686 observations				
<b>Panel C: Subsidy statistics for a 22-km carpooling journey</b>					
Carpooling gains of drivers(€)	2.17	2.20	0	2.5	0.15
Carpooling costs of passengers (€)	0.49	0.50	0	1.35	0.47
Net subsidy(€)	1.68	1.70	0	2.2	0.47
Number of observations	400 of 1123 cities groups have subsidy incentives				

Notes: The carpooling data in Panel B is constructed from Panel A. The Unit of population density is the number of people per square kilometer. The unit of duration is minute. The unit of distance is meter. The net subsidy for a carpooling trip in Panel C comes from “Carpooling gains of drivers” minus “Carpooling costs of passengers”.

## 5. Econometric strategy

### 5.1. Check on parallel trend assumption

Before making a two-way fixed effect (TWFE) estimation as described below, we should first test if our data satisfies the parallel trends assumption between treated and control groups. That is, in the absence of carpooling subsidies, the growth in the carpooling usage would be the same across treated and control groups. To be specific, we consider a 25-month window, spanning from 10 months before subsidy incentives until 15 months after subsidy.

We test this in a flexible model by adding month-dummies in the regression to trace out the time effect of carpooling subsidy on the carpooling usage. The regression function is shown in equation (1).

$$y_{st} = \alpha + \sum_{i=1}^{10} \varphi_i \cdot D_{st}^{-i} + \sum_{j=1}^{15} \tau_j \cdot D_{st}^{+j} + A_s + B_t + \varepsilon_{st} \quad (1)$$

where the dummy variables  $D_{st}^{-i}$  are lags and  $D_{st}^{+j}$  leads dummies. We estimate the dynamic effect of local incentives on trip behavior excluding  $D^0$  which is the month the local carpooling subsidy starts.  $A_s$  and  $B_t$  are cities group and month fixed effects.  $\varepsilon_{st}$  is residual error term. Thus, the parallel trend assumption holds if  $\varphi_i=0$ .

In addition to the parallel trend assumption, another underlying assumption for TWFE is that the selection of treatment groups is random and the treatment is exogenous. Yet the selection of cities groups that implemented carpooling subsidies may not be random. To control for this potential estimation bias, we conducted propensity score matching as in [Cui et al. \(2023\)](#) and [Zheng et al. \(2022\)](#). Results are displayed in Appendix A.1 and show our framework is not affected by this bias.

### 5.2. Baseline model

The two-way fixed effect (TWFE) model is a frequently employed statistical method to evaluate policy effectiveness ([Bo, 2020](#); [Ren et al., 2023](#); [Zheng et al., 2022](#)). By studying differential effect of a treatment on a ‘treatment group’ versus a ‘control group’ in a natural experiment, it

can estimate the changes in the outcome variable that occur over time between the treatment and control group. The fact that implementations of carpooling subsidies in different cities groups over time is a shock on carpooling makes itself a quasi-natural experiment. In this way, we can examine the data using a TWFE approach by comparing how carpooling usage changes in cities groups when there are carpool subsidies relative to changes in cities groups where there are no carpool subsidies.

The core of this study is to empirically estimate the impact of carpooling subsidies on carpooling usage. Carpooling subsidies were implemented in different cities groups at distinct times. Thus, a time-varying TWFE model is as follows:

$$y_{st} = \alpha + \beta \cdot policy_{st} + A_s + B_t + \varepsilon_{st} \quad (2)$$

$$y_{st} = \alpha + r \cdot subsidy_{st} + A_s + B_t + \varepsilon_{st} \quad (3)$$

In equation (2),  $s$  denotes the cities group,  $t$  denotes year-month,  $y_{st}$  represents number of carpooling trips per thousand inhabitants in cities group  $s$  at year-month  $t$ . We adjust carpooling usage by dividing population and then multiplying by 1000 to make estimates easy to interpret.  $D_{st}$  is the dummy variable indicating carpooling subsidy policy, which is 1 if there is a carpool incentive in cities group  $s$  at year-month  $t$  and 0 otherwise. The coefficient  $\beta$  is the policy effects estimator. It is the difference in carpooling usage of the cities groups that have carpooling subsidies policy relative to the control group.  $A_s$  and  $B_t$  are cities group and year-month fixed effects.  $\varepsilon_{st}$  is residual error term. In equation (3), other things are the same, but we replace the treatment variable  $policy_{st}$  by  $subsidy_{st}$ , a continuous variable which is the amount of carpooling subsidy in cities group  $s$  at year-month  $t$ . So the coefficient  $r$  shows how many carpooling usage would be increasing with an extra one euro subsidy. The parameters of interest are  $\beta$  and  $r$ .

### 5.3. Time effect model

The treatment effects of subsidy policies on carpooling usage may not be static in time, thus we examine the dynamics of the relationship between local incentive policies and carpooling usage. We introduce interaction time effects with the specifications described in equations (4) to (7).

$$y_{st} = \alpha + policy_{st} \cdot (\beta_1 + \beta_2 \cdot diff) + A_s + B_t + \varepsilon_{st} \quad (4)$$

$$y_{st} = \alpha + policy_{st} \cdot (\beta_1 + \beta_2 \cdot diff + \beta_3 \cdot diff^2) + A_s + B_t + \varepsilon_{st} \quad (5)$$

$$y_{st} = \alpha + subsidy_{st} \cdot (\beta_1 + \beta_2 \cdot diff) + A_s + B_t + \varepsilon_{st} \quad (6)$$

$$y_{st} = \alpha + subsidy_{st} \cdot (\beta_1 + \beta_2 \cdot diff + \beta_3 \cdot diff^2) + A_s + B_t + \varepsilon_{st} \quad (7)$$

$diff$  is the time difference between the year-month  $t$  and the implementation time of carpooling subsidy.  $\beta_1$  in equation (4) (respectively (6)) measures if the treatment effect (resp. subsidy amount effect) decreases, increases or is stable over time.  $\beta_3$  in equation (5) and (7) measures if this time variation amplifies or retracts over time.

#### 5.4. Heterogeneity model

Another research question of interest stands in the potential sources of heterogeneity in the subsidy effects. We specify this heterogeneity in the following manner. For each of the possible sources of heterogeneity variable we split the sample evenly into four quartiles and created four dummies  $Q_1, Q_2, Q_3$  and  $Q_4$ . For example, if the value lies in the second interval, then  $Q_2 = 1$  and  $Q_1 = Q_3 = Q_4 = 0$ . We then introduce interactions between the subsidy effect and the quartile dummies:

$$y_{st} = \alpha + policy_{st} \cdot (\beta_1 + \beta_2 \cdot Q_2 + \beta_3 \cdot Q_3 + \beta_4 \cdot Q_4) + A_s + B_t + \varepsilon_{st}. \quad (8)$$

$$y_{st} = \alpha + subsidy_{st} \cdot (\beta_1 + \beta_2 \cdot Q_2 + \beta_3 \cdot Q_3 + \beta_4 \cdot Q_4) + A_s + B_t + \varepsilon_{st}. \quad (9)$$

$Q_1$  is the omitted variable so that  $\beta_1$  is the benchmark coefficient. Coefficients of interest are  $\beta_2, \beta_3$  and  $\beta_4$ .

## 6. Effects of subsidy on carpooling usage

### 6.1. Parallel trend test

Figure 5 plots the dynamic marginal treatment effects of the subsidy incentive effects on carpooling usage before and after the implementation. We take the year-month time of the subsidy implementation as the base time  $D^0$ . The regression coefficient and 95% confidence intervals for every coefficient are shown in the figure. In the x-axis, 0 represents the time policies are

implemented. The right and left side of 0 are the months after and before the implementation time. Specifically, we examine a 25-month window, spanning from 10 months before the carpooling subsidy until 15 months after the implementation. On the left side of Figure 5, we find that coefficients on the carpooling subsidy dummy variables fluctuate around 0, while on the right side, coefficients are significantly different from zero and increase over time after the policy implementation<sup>20</sup>. It shows that the treated cities groups and control cities groups are not significantly different before the implementation of the subsidy policy. We conclude that the parallel trend assumption holds.

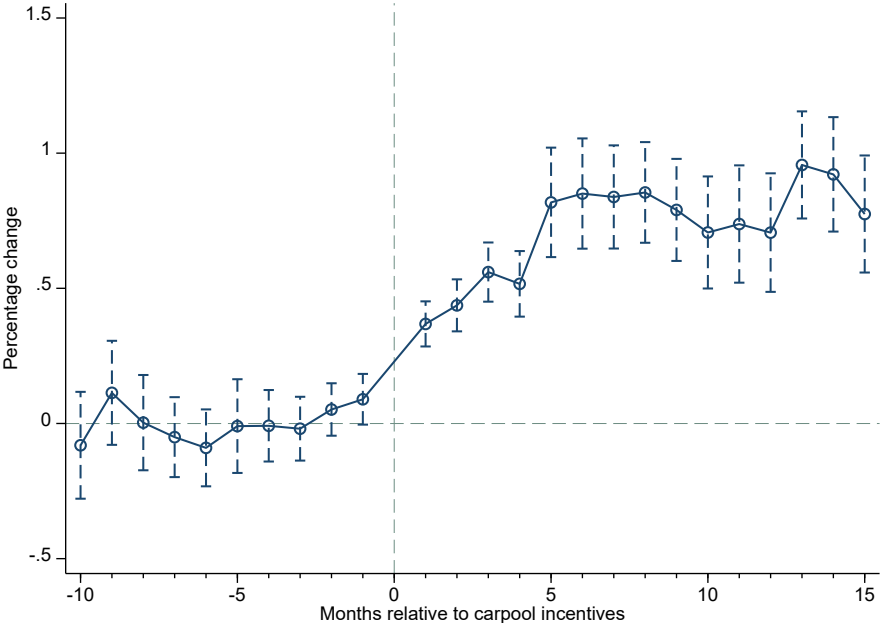


Figure 5. Effect of subsidy on log number of carpool trips per inhabitant before and after implementation

Notes: This figure plots the effect of local carpool subsidies on the log number of carpool trips per inhabitant in cities groups. We consider a 25-month window, spanning from ten months before the implementation of the incentive until fifteen months after the implementation of the incentive. The dashed lines are 95% confidence intervals, adjusted for cities group-level clustering.

<sup>20</sup> We should note that the coefficient  $\varphi_{-1}$  (first lag month) is almost statistically positive in Figure 5. It is because as most cities groups did not have official documents showing when the subsidy policy started, we use the earliest news release date as the start time of the subsidy when this start time was not officially specified. As a result, the policy start time may be slightly lagging for one month.

## 6.2. Baseline regression results

Table 2 shows the regression results with the full sample using the TWFE approach. Specifically, the independent variable is the monthly carpooling volume per 1000 inhabitants (e.g.,  $1000 \times$  monthly trip volume in cities groups / population). We estimate the effect of the implementation of the policy (*policy* variable) and the amount of subsidy (*subsidy* variable) on carpooling usage. Results are shown in columns (1) and (2) of Table 2, respectively. In this case, *policy* is a dummy variable that takes the value of 1 when the cities group has a carpooling subsidy policy. *subsidy* is a continuous variable equal to the amount of subsidy for a 22km carpooling journey in the cities group.

Table 2. Average treatment effect with full sample

Dependent variable	(1) carpooling trips/1000 in- habitants	(2) carpooling trips/1000 in- habitants
policy	5.504*** (4.71)	
subsidy		3.943*** (4.85)
Constant	7.524*** (18.75)	6.800*** (13.29)
Observations	20,686	20,686
R-squared	0.264	0.276
Number of cities groups	1,123	1,123
Year-month fixed effects	Yes	Yes
Cities groups fixed effects	Yes	Yes

Notes: This table reports the estimators of  $\beta$  and  $r$  from Equation (1) and (2), using fixed-effects panel data model. We control year-month and cities groups fixed effects in both models. Dependent variable is the number of carpooling trips per thousand inhabitants. Standard errors are clustered at the cities group level. In parentheses are the robust t-statistics clustered at the cities group level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

We use year-month and cities groups fixed effects. We find that there is a high and statistically significant correlation between carpooling subsidies and the usage of carpooling in France. Specifically, column (1) results show that the implementation of local carpooling subsidies on average increases carpooling usage by around 5.5 carpooling trips/month per 1000 inhabitants. Column (2) results show that a one-euro increase in carpooling subsidy leads to an extra 3.9

trips per 1000 inhabitants. We further conduct a series of robustness tests on the baseline regression estimations in Appendix A.2 to A.5, including using PSM-TWFE, replacing the dependent values, using other estimators, doing a bacon decomposition and also a placebo test. These robustness tests show results are consistent with the estimations reported in Table 2.

### 6.3. Time effect analysis

We run regression as shown in equations (4-7) above to estimate changes of subsidy effects over time. Equations (4-7) include linear and quadratic time trends to two-way fixed effects models. The estimation results are shown in Table 3. Comparing the adjusted R-squared between the linear and the quadratic model, or by checking the statistical significance of the quadratic term's coefficient in Table 2 and Table 3, we find equations (5) and (6) are better on the fit of models.

Results in column (1) from Table 3 show that the implementation of carpooling subsidy became effective just after the introduction of the policy ( $\widehat{\beta}_1 = 2.523$ ). Besides, the subsidy effect increases in the following months at an average rate of 0.15 carpooling trips per month per 1000 inhabitants. However, column (2) suggests that this growth diminishes over time, as the quadratic term's coefficient is negative and significant at 10% (-0.008 in column (2)). These results suggest that the implementation of carpooling subsidies becomes more efficient over time. In the same vein, columns (3) and (4) estimation results show that the stimulating effect on carpooling usage of an extra 1-euro subsidy increases over time, yet there is no significant quadratic time effect in column (4).



Table 3. Time effect of subsidy

Dependent variable	(1) carpooling trips/1000 inhabitants	(2) carpooling trips/1000 inhabitants	(3) carpooling trips/1000 inhabitants	(4) carpooling trips/1000 inhabitants
policy	2.523** (2.49)	0.226 (0.25)		
policy×diff	0.149** (2.58)	0.492** (2.32)		
policy×diff <sup>2</sup>		-0.008* (-1.86)		
subsidy			2.569*** (3.21)	1.523** (2.55)
subsidy×diff			0.076*** (2.63)	0.227** (1.97)
subsidy×diff <sup>2</sup>				-0.003 (-1.53)
Constant	10.792*** (6.45)	11.769*** (7.72)	8.603*** (4.20)	9.177*** (4.96)
Observations	9,422	9,422	9,422	9,422
R-squared	0.342	0.350	0.350	0.355
Number of cities groups	400	400	400	400
Year-month fixed effects	Yes	Yes	Yes	Yes
Cities groups fixed effects	Yes	Yes	Yes	Yes

Notes: This table reports the estimates of  $\beta$  from equation (4-7). All regressions include year-month fixed effects and cities groups fixed effects. The independent variable is the value of the monthly carpooling volume per 1000 inhabitants. Standard errors are clustered at the cities group level. In parentheses are the robust t-statistics clustered at the cities group level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

## 7. Heterogeneity in carpooling subsidy effect

The previous section shows strong evidence that local carpooling subsidies have statistically significant effects on carpooling usage across France. This section examines the heterogeneity of subsidy effects across cities groups with different socioeconomic characteristics. We consider three potential sources of heterogeneity: population, density and income. We use the model described in Equation (8) and (9) to test for these heterogeneity sources.

### 7.1. Cities group population heterogeneity effect

We estimate equations (8) and (9) with cities group population as the variable split in quartiles. Table 4 reports the estimation of the effect of the carpooling policy and different subsidy

amounts on carpooling usage across cities groups population quartiles. Estimation coefficients for the first quartile population of cities group are negative and significant statistically, both for independent variables of *policy* and *subsidy*. We should note that the negativity of  $\widehat{\beta}_1$  does not mean that the implementation carpooling subsidy or one extra euro of subsidy has negative effects on carpooling usage in small-sized cities groups. Remember that the control group contains cities groups of all sizes. This means that the control group's carpooling usage is larger than those small cities groups with carpooling subsidies.

Table 4. Subsidy effects on different population

Dependent variable	(1) carpooling trips/1000 inhabit- ants	(2) carpooling trips/1000 inhabit- ants
policy	-1.551** (-2.46)	
Q <sub>2</sub> pop2020 × policy	0.395 (0.48)	
Q <sub>3</sub> pop2020 × policy	6.303*** (2.77)	
Q <sub>4</sub> pop2020 × policy	9.103*** (4.62)	
subsidy		-1.175*** (-3.06)
Q <sub>2</sub> pop2020 × subsidy		0.635 (1.05)
Q <sub>3</sub> pop2020 × subsidy		4.688*** (3.04)
Q <sub>4</sub> pop2020 × subsidy		5.950*** (4.87)
Constant	7.845*** (20.09)	7.299*** (15.59)
Observations	20,686	20,686
R-squared	0.273	0.283
Number of cities groups	1,123	1,123
Year-month fixed effects	Yes	Yes
Cities groups fixed effects	Yes	Yes

Notes:  $Q_i pop2020 (i \in (2,3,4))$  is a series of dummy variables indicating if the cities group belongs to the second (third/fourth) quantile of population. 4th quantile cities groups have the largest population size, and 1st quantile cities groups the smallest. All regressions include year-month fixed effects and cities groups fixed effects. The independent variable is the value of the monthly carpooling volume per 1000 inhabitants. Standard errors are clustered at the cities group level. In parentheses are the robust t-statistics clustered at the cities group level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

We also find that treatment coefficients increase with cities group population. It implies that the efficiency of the subsidy increases with cities group population. A possible explanation for this result is that there is a network effect in carpooling usage. When more drivers choose to carpool, it will attract more passengers, and more carpooling passengers will attract more drivers to join the carpool. Thus it exhibits an effect of increasing marginal scale as the city group's population increases, and so does the subsidy effect.

## 7.2. Density heterogeneity effect

We measure the density of a cities group as the ratio of the total population on its total area (Mindali, 2004). Cities can be seen as places of concentration of social and economic activities connected by transport networks (Cheng et al., 2013). The higher the density of a cities group, the more complex and denser the transportation network (Yin et al., 2023). Density is a more rational reflection of the measure of network effect than the use of population size. Therefore, this subsection further estimates the heterogeneous subsidy effects over cities groups with different population densities.

We estimate equations (8) and (9) with cities group density as the variable to split in quartiles. Results in Table 5 show that the treatment effects are significant and increase with the density of cities groups. This further strengthens our hypothesis in subsection 7.1. Carpooling platforms, as a two-sided platform, have a larger subsidy effect with larger density due to the direct network benefits between drivers and passengers.

Table 5. Subsidy effects on different density

Dependent variable	(1) carpooling trips/1000 in- habitants	(2) carpooling trips/1000 in- habitants
policy	-2.156*** (-3.86)	
Q <sub>2</sub> density2020 × policy	2.728 (1.09)	
Q <sub>3</sub> density2020 × policy	6.146*** (4.08)	
Q <sub>4</sub> density2020 × policy	10.324*** (4.79)	
subsidy		-1.849*** (-3.98)
Q <sub>2</sub> density2020 × subsidy		2.749 (1.47)
Q <sub>3</sub> density2020 × subsidy		4.658*** (4.45)
Q <sub>4</sub> density2020 × subsidy		6.993*** (5.03)
Constant	7.695*** (19.53)	7.131*** (14.96)
Observations	20,686	20,686
R-squared	0.273	0.284
Number of cities groups	1,123	1,123
Year-month fixed effects	Yes	Yes
Cities groups fixed effects	Yes	Yes

Notes:  $Q_i$ density2020 ( $i \in (2,3,4)$ ) is a series of dummy variables indicating if the cities group belongs to the second (third/fourth) quantile of density. All regressions include year-month fixed effects and cities groups fixed effects. The independent variable is the value of the monthly carpooling volume per 1000 inhabitants. Standard errors are clustered at the cities group level. In parentheses are the robust t-statistics clustered at the cities group level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

### 7.3. Income heterogeneity effect

The economic level of a city's population is an important factor to be considered when implementing incentive policies. The policy effects can vary considerably across people with different income levels, such as setting congestion prices (Eliasson & Mattsson, 2006), passenger transport subsidies (Tsharaktshiew & Hirte, 2012) and license plate regulations (Wang & Zhao, 2017). Moreover, different income levels of carpoolers are involved in a carpooling trip.

Usually, high-income level carpoolers serve as drivers whereas low-income carpoolers are carpool passengers (Shaheen et al., 2017). It is unclear whether there is variability in the effect of carpooling subsidies in cities with high and low average income levels. In this subsection, we examine the heterogeneous subsidy effect among cities groups of median disposable income.

As Table 6 shows, the subsidy does not show a monotonous variation with the income level of cities group. We further divide all cities groups into ten deciles according to median disposable income in Appendix C and examine the heterogeneity of policy effects following the same methodology. This confirms that the subsidy effect does not vary monotonously with income.

Table 6. Subsidy effects on different income

Dependent variable	(1) carpooling trips/1000 in- habitants	(2) carpooling trips/1000 in- habitants
policy	0.155 (0.15)	
$Q_2income2020 \times policy$	7.607 (1.50)	
$Q_3income2020 \times policy$	8.414*** (3.42)	
$Q_4income2020 \times policy$	4.207** (2.39)	
subsidy		0.896 (1.16)
$Q_2income2020 \times subsidy$		5.268 (1.48)
$Q_3income2020 \times subsidy$		4.860*** (3.17)
$Q_4income2020 \times subsidy$		1.643 (1.48)
Constant	7.598*** (19.45)	6.979*** (15.06)
Observations	20,686	20,686
R-squared	0.273	0.286
Number of cities groups	1,123	1,123
Year-month fixed effects	Yes	Yes
Cities groups fixed effects	Yes	Yes

Notes:  $Q_iincome2020(i \in (2,3,4))$  is a series of dummy variables indicating if the cities group belongs to the second (third/fourth) quantile of median disposable income. All regressions include year-month fixed effects and cities groups fixed effects. The independent variable is the value of the monthly carpooling volume per 1000 inhabitants. Standard errors are clustered at the cities group level. In parentheses are the robust t-statistics clustered at the cities group level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

## 8. Conclusion and policy implication

To encourage more use of carpooling, the French local authorities implemented a set of measures to encourage carpooling, including strong monetary incentives in the form of subsidies. This study aims to shed light on the promotion of carpooling by estimating the effects of government subsidies on short-distance carpooling ridership in the French market.

We complement existing literature by investigating the causal relationship between local government incentives and carpooling behavior. Based on panel data from 1123 cities groups in France from 2019 to 2023, this study investigates the effect of carpooling subsidies on its usage. A two-way fixed effect model is used to estimate the treatment effects from a natural experiment. The treated groups are the cities groups that have implemented carpooling incentives, while the control groups comprise cities groups that have no carpooling subsidies. We avoid the potential endogeneity problem due to the biased selection of cities groups by using a series of robustness tests.

The baseline results provide evidence that the local carpooling incentives have a significantly positive effect on carpooling usage in France. We estimate an increase of 5.5 carpooling trips per thousand inhabitants monthly in cities groups. A one-euro increase in carpooling subsidy leads to another 3.9 trips per thousand inhabitants. Besides, the time effect analysis shows that the effect of the implementation of local incentives is strengthened over time, but its growth diminishes over time. Moreover, the presence of carpooling incentives has a larger effect on carpooling usage in large-sized and high-population-density cities groups than in small-sized and low-density cities groups.

Our estimation implies that carpooling subsidies are effective in improving carpooling on platforms, yet the data do not allow us to identify if new carpoolers come from non-platform carpooling, private cars or public transportation. Therefore, the comparison of such a subsidy with other policy initiatives such as providing HOV infrastructure or free parking access for carpoolers is difficult. But from the perspective of policymakers, we find the impact of the carpooling subsidy gets more effective over time. Thus we recommend policymakers to be patient with subsidy policies because policy effects are more effective in the long-term future. Besides, the subsidy effects are different across the density and population size of the cities group. This suggests that subsidy policies should be formulated in relation to these characteristics of cities groups, rather than all cities groups formulating the same subsidy policies. Moreover, we find that subsidy effects do not vary with the income level of the city, and therefore income is a less important city characteristic to consider when formulating subsidy or similar policies.

Finally, this study has several limitations and thus raises some possible research questions that deserve future exploration. First, due to the lack of data, this study only analyzes net subsidy for one carpooling trip, yet if subsidy effects are the same for drivers and passengers remain unknown. In future studies, we may use theoretical methods or other datasets to further examine carpooling subsidy effects. Second, our estimation only shows subsidy effects on carpooling platform usage. As mentioned before, carpooling on the platform is only a small portion of the total carpooling usage. Private carpooling that happens between friends, family, or colleagues may move to platforms for obtaining subsidies. Thus our result could overestimate the overall carpooling subsidy effect. More detailed data is needed to further estimate subsidy effects on the overall carpooling usage. Finally, this study lacks a systematic mechanism for testing in subsidy effects estimation. For example, it is unclear why the effect of carpooling subsidies increases over time. It might be because people build environmental awareness over time. In this way, carpooling subsidies will be less needed in the future. Yet we still need to make some mechanism analysis. We may be able to combine the two-way fixed effect model and instrumental variables approach in the future to better address the problem.



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## Appendix A. Robustness test

### A.1. PSM-TWFE method

A major concern for identifying the subsidy effects of carpooling is that local government might decide to implement a subsidy policy that is better suited for carpooling promotion. To eliminate this selection bias and test the robustness of our previous estimation, we conduct a propensity score matching and two-way fixed effects (PSM-TWFE) strategy. We focus on cities groups with similar socio-economic characteristics, in terms of share of young people (*younger\_than\_25*), log of population (*ln\_pop*), share of service industry (*industry*), and share of car ownership (*car\_owner*).

Figure 6 provides the balanced test of variables before and after PSM. We can see that the standardized bias across variables declines significantly to within 26% after matching, indicating there is no significant difference between treated and controlled groups.

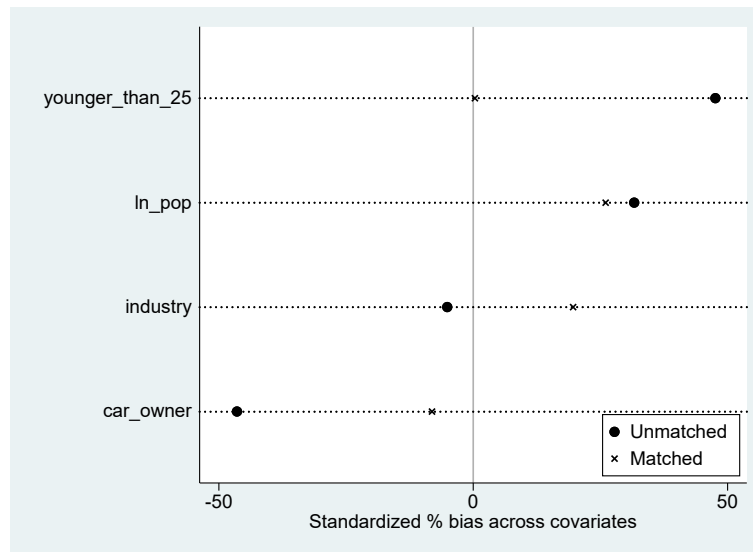


Figure 6. Balanced test of variables before and after PSM

Notes: This figure plots the percentage of standardized bias across covariates before and after propensity score matching.

Figure 7 displays the distribution of propensity scores of our controlled and treated groups. It shows that 309 cities groups are excluded from the analysis because that they fail to meet the common support assumption, either of the too high or too low probability of implementing carpooling subsidy policies.

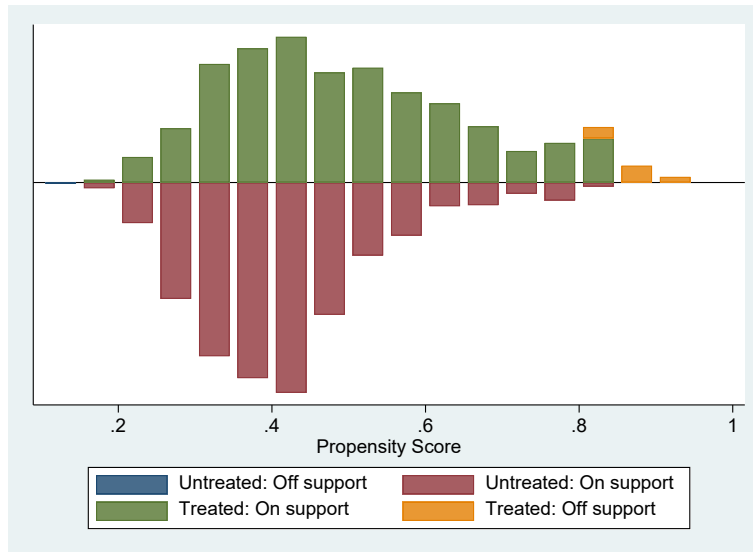


Figure 7. Propensity score distribution of treated and controlled groups

Notes: This figure plots propensity score of treated and controlled groups. Samples that are off support are removed from our PSM-TWFE analysis.

Figure 8 reports the Kernel density distribution of propensity score before and after matching. After matching, the distance between the mean lines of the kernel density is shortened. In addition, the two kernel density distribution curves are closer, so PSM reduces sample selectivity bias.

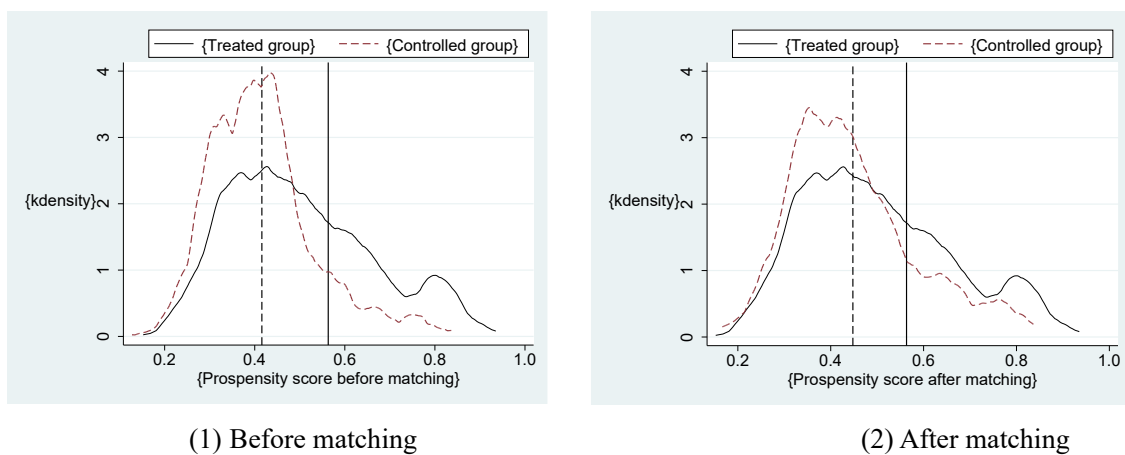


Figure 8. Kernel density distribution of propensity score before matching

After eliminating systematic differences between our controlled groups and treated groups based on socio-economic characteristics, we further conduct the TWFE model to estimate policy effects. Estimation results with PSM-TWFE are shown in Table 7. These results are consistent with the previous estimation results in Table 2.

Table 7. Robustness check of the PSM-TWFE approach

Dependent variable	(1) carpooling trips/1000 in- habitants	(2) carpooling trips/1000 in- habitants
policy	5.513*** (4.72)	
subsidy		3.949*** (4.85)
Constant	7.487*** (18.88)	6.790*** (13.57)
Observations	20,377	20,377
R-squared	0.262	0.274
Number of cities groups	1,115	1,115
Year-month fixed effects	Yes	Yes
Cities-groups fixed effects	Yes	Yes

Notes: This table reports the estimation results using PSM-TWFE approach. We control year-month and cities groups fixed effects in both models. Dependent variable is the number of carpooling trips per thousand inhabitants. Standard errors are clustered at the cities group level. In parentheses are the robust t-statistics clustered at the cities group level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

## A.2. Alternative dependent variables

In the previous section, we use the number of trips taken using carpooling in the monthly cities group as the dependent variable. To verify the robustness of the regression results, we replace the dependent variables with the total duration (i.e., column (1-2) in Table 8) and total distance traveled (i.e., column (3-4) in Table 8) for monthly carpooling trips per inhabitant in cities groups. The results, shown in Table 8, show consistency with the previous basic regression results in Table 2, which validates the robustness of our results.



Table 8. Effect of carpooling subsidy on monthly carpooling duration and distance

Dependent variable	(1) carpooling trips duration/ inhabitant	(2) carpooling trips duration/ inhabitant	(3) carpooling trips distance/ inhabitant	(4) carpooling trips distance/ inhabitant
policy	0.125*** (4.29)		105.957*** (4.70)	
subsidy		0.089*** (4.42)		76.315*** (5.00)
Constant	0.199*** (19.00)	0.183*** (13.79)	205.495*** (22.65)	191.223*** (17.64)
Observations	20,686	20,686	20,686	20,686
R-squared	0.275	0.284	0.314	0.323
Number of cities groups	1,123	1,123	1,123	1,123
Year-month fixed effects	Yes	Yes	Yes	Yes
Cities groups fixed effects	Yes	Yes	Yes	Yes

Notes: This table reports the estimation results of subsidy on monthly carpooling duration and distance per inhabitant in cities groups. The dependent variable for the first two columns is carpooling trips duration/population. The dependent variable for the last two columns is carpooling trips distance/population. We control year-month and cities groups fixed effects in both models. Standard errors are clustered at the cities groups level. In parentheses are the robust t-statistics clustered at the cities groups level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.

### A.3. Placebo tests

We further conduct a placebo counterfactual test to check the robustness of our previous estimations. We do this by randomly assigning the subsidy implementation time and treating cities groups. Then we repeat the benchmark regression 500 times and get the distribution of the coefficient and p-value. Results are shown in Figure 9. The mean value of these random estimates is around 0 and between -1 to 2, while our estimate is 5.5, indicating that our estimates are not likely to be severely biased due to omitted variables.

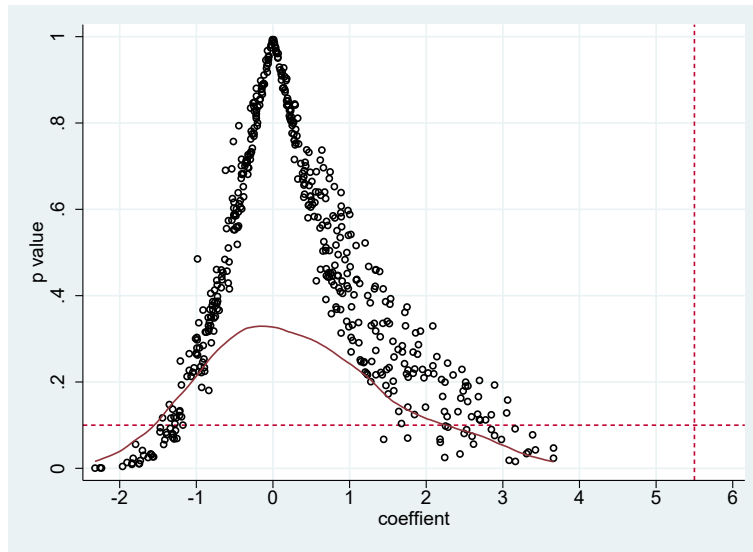


Figure 9. Placebo tests

Notes: This figure shows the kernel density distribution of placebo tests coefficients. The dots are corresponding p values.

#### A.4. Other estimators

According to (Sun & Abraham, 2021), only under some strong assumptions of treatment effect homogeneity, TWFE using OLS can deliver consistent estimates. To deal with heterogeneity in treatment effects across time and treated units, we further use some recently proposed estimators that are robust with treatment heterogeneity (Borusyak et al., 2021; Callaway & Sant'Anna, 2021; De Chaisemartin & d'Haultfoeuille, 2023). Figure 10 shows event study figure by using these estimators. It shows that the estimates are consistent with Figure 5 and the parallel trends assumption holds.

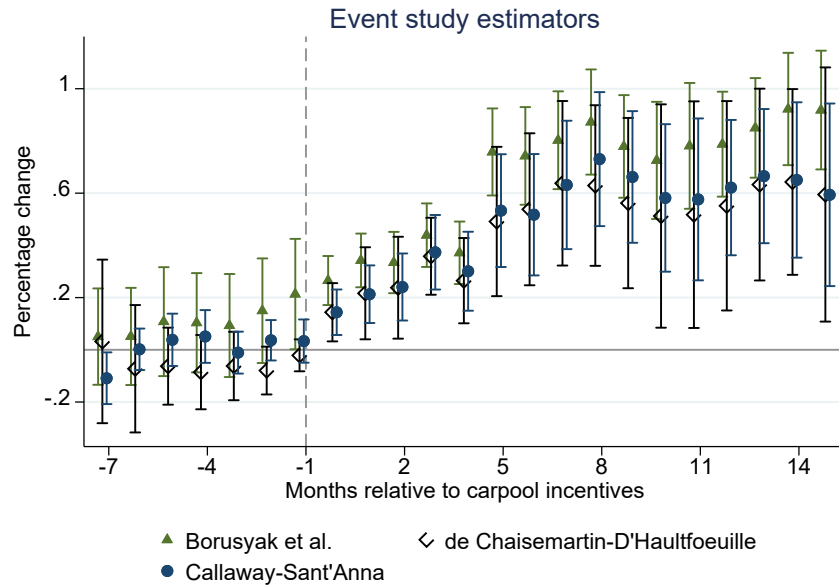


Figure 10. Other estimators

Notes: This figure presents the event-study plots constructed using three different estimators: Borusyak et al., (2021) (in green with triangle markers); Callaway and Sant'Anna (2021) (in blue with dot markers); De Chaisemartin and d'Haultfoeuille (2023) (in black with square markers). We find the estimation results are consistent with Figure 5.

#### A.5. Bacon decomposition

For the reason of heterogeneity in the treatment effects of the staggered timing regressions, which may lead to forbidden comparisons (two sets of already treated units) and negative weighting issues. We further conduct a bacon decomposition test proposed by Baker et al., (2022) to examine the bias of multiple time-point double difference estimates. **Erreur ! Source du renvoi introuvable.** shows the result of Bacon decomposition. We find that the weight of the appropriate treatment effect is 65.1%, and the treatment effect is 8.289. The weight of the forbidden treatment effect is relatively small. Thus the previous estimation results are robust.

Table 9. Bacon decomposition results

DD Comparison	Weight	Avg DD Est
Earlier T vs. Later C	0.059	3.883
Later T vs. Earlier C	0.066	-1.242
T vs. Never treated	0.651	8.289
T vs. Already treated	0.224	1.159
T = Treatment; C = Comparison		

Notes: In Bacon decomposition analysis, we take the number of carpooling trips per thousand inhabitants as the dependent variable. The implementation of the subsidy policy (dummy variable) is the independent variable. Year-month and cities groups fixed effects are controlled.

## **Appendix B. Estimating carpooling subsidy implementation**

Table 10 and Table 11 show regression results of the potential determinants of when and whether the carpooling incentives would be implemented in cities groups.

Table 10 reports the results of linear regressions predicting if cities groups has a subsidy policy. Except for the log of median disposable income, the P-values of other socioeconomic variables are all lower than 0.1, indicating that these variables are statistically significant at a 10% error level. Among them, the cities groups' population is the dominant predictor for the implementation of carpooling incentives and such an effect is significantly positive. It seems that if cities groups have large-sized populations, they're more likely to implement subsidy policies. Because a larger population means more demand for carpools, the government will be more inclined to take relevant policy measures. Additionally, the share of young people in cities groups is positively related to the existence of the policy. This implies that the younger people there are in a cities group, the more carpoolers, the more likely the city is to implement carpool subsidy policies. Previous online survey shows that carpoolers are on average younger than the overall population and students are frequent users in France (Shaheen et al., 2017). This result is consistent with the literature. Another determinant is the share of car ownership. When a cities group has more households that have cars, these people can use their own car instead of carpooling to travel. Private cars are a substitute for carpooling. Consistent with our common sense, this regression coefficient is significantly negative.

Meanwhile, the share of the service industry is negatively related to whether a cities group has carpooling incentives. We know that the share of the service industry is the percentage of commerce, transport, accommodation, and catering in business creations. A possible explanation would be that in places with a more developed service industry, the transport infrastructure will be more complete. People prefer to use public transportation instead of carpooling, which decreases the utilization of carpooling in the area. Thus the local government has little motivation

to implement carpooling subsidy policies. Moreover, median disposable income has no relationship with the implementation of the incentives. It could be explained by the different income levels of carpoolers involved in a carpooling trip. Usually, high-income carpoolers serve as drivers whereas low-income carpoolers are carpool passengers, as in (Shaheen et al., 2017). Consequently, median disposable income is not significant to predict if the cities group tends to encourage carpool.

Table 10. Linear regressions predicting whether the carpooling incentives would be implemented in cities groups

Dependent variable	(1) Has incentive	(2) Has incentive	(3) Has incentive	(4) Has incentive	(5) Has incentive
ln(population)	0.083*** (5.63)	0.080*** (5.44)	0.064*** (3.88)	0.033* (1.84)	0.038** (2.11)
ln(median disposable income)		0.210 (1.45)	0.113 (0.75)	0.072 (0.48)	-0.113 (-0.68)
Share of young people			0.010** (2.23)	0.011** (2.51)	0.013*** (2.88)
share of car ownership				-0.010*** (-4.29)	-0.011*** (-4.65)
share of service industry					-0.008*** (-2.61)
Constant	-0.491*** (-3.25)	-2.572* (-1.78)	-1.709 (-1.14)	-0.215 (-0.14)	1.810 (1.06)
Observations	1,123	1,123	1,123	1,123	1,123
R-squared	0.027	0.029	0.034	0.049	0.055

Notes: This table reports the OLS regression results for predicting if a cities group has carpooling incentives. The dependent variable is a binary indicator if the cities group has a carpooling subsidy policy. Independent variables are the log of population (2020), the log of median disposable income (2020), share of young people (2020), share of car ownership (2020) and share of service industry (2022). Among them, share of young people is the percentage of the population aged younger than 25; the share of car ownership is the percentage of households with at least 1 car in 2020; share of service industry is the percentage of commerce, transport, accommodation and catering in business creations in 2022. T-statistics are in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 11 further presents the linear regression statistics for predicting the implementation date of carpooling incentives. We observe that all the above-mentioned variables are statistically

significant at a 1% error level. Population, income and share of young people are the three strongest predictors of how early the carpooling incentives are implemented. The cities groups that implemented the carpooling subsidy policy earlier are characterized by a larger population, a larger median disposable income, a larger percentage of young people, and a more developed service sector. In addition, when more people in the cities group own cars, the later the city implements the subsidy. The interpretation of these estimates is similar to that of the previous table.

Combining with the estimation results in Table 10, we hypothesize that subsidy effects might be different among cities groups of different socioeconomic characteristics. This is our justification for choosing these socioeconomic characteristics to do the PSM-TWFE.

Table 11. Linear regressions predicting when the carpooling incentives would be implemented in cities groups

Dep. Variables	(1) Start date	(2) Start date	(3) Start date	(4) Start date	(5) Start date
ln(population)	-3.198*** (-4.07)	-2.107*** (-2.75)	0.940 (1.15)	3.263*** (3.70)	3.650*** (4.12)
ln(median disposable income)		-48.777*** (-6.49)	-27.363*** (-3.63)	-20.130*** (-2.74)	-29.678*** (-3.66)
Share of young people			-1.858*** (-7.70)	-1.913*** (-8.24)	-1.835*** (-7.91)
share of the car owner				0.565*** (5.83)	0.507*** (5.15)
share of service industry					-0.444*** (-2.70)
Constant	771.320*** (93.24)	1,248.199*** (16.89)	1,053.646*** (14.34)	912.736*** (12.23)	1,017.342*** (12.17)
Observations	400	400	400	400	400
R-squared	0.040	0.132	0.245	0.305	0.318

Notes: This table reports the linear regression results for predicting when a cities group has carpooling incentives. The dependent variable is the start date of the policy implementation. The larger the value of the start date, the later the incentive starts to be enforced. Independent variables are the same as in the previous table. T-statistics are in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## Appendix C. Heterogeneity of income

We divide all cities groups into ten equal parts according to median disposable income as in section 7.3 and further examine the heterogeneity of policy effects. This confirm that the subsidy effect does not vary monotonously with income.

Table 12. Heterogeneity of income in decile

Dependent variable	(1) carpooling trips/1000 in- habitants	Dependent variable	(2) carpooling trips/1000 in- habitants
policy	0.657 (0.38)	subsidy	1.506 (1.40)
Q <sub>2</sub> pop2020 × policy	-1.320 (-0.63)	Q <sub>2</sub> pop2020 × subsidy	-1.632 (-1.20)
Q <sub>3</sub> pop2020 × policy	-0.107 (-0.06)	Q <sub>3</sub> pop2020 × subsidy	-0.953 (-0.84)
Q <sub>4</sub> pop2020 × policy	-1.132 (-0.57)	Q <sub>4</sub> pop2020 × subsidy	-1.382 (-1.08)
Q <sub>5</sub> pop2020 × policy	14.344 (1.59)	Q <sub>5</sub> pop2020 × subsidy	8.643 (1.61)
Q <sub>6</sub> pop2020 × policy	9.164** (2.11)	Q <sub>6</sub> pop2020 × subsidy	4.710* (1.71)
Q <sub>7</sub> pop2020 × policy	8.218** (2.46)	Q <sub>7</sub> pop2020 × subsidy	4.759** (2.49)
Q <sub>8</sub> pop2020 × policy	-1.350 (-0.73)	Q <sub>8</sub> pop2020 × subsidy	-1.764 (-1.58)
Q <sub>9</sub> pop2020 × policy	6.741** (2.14)	Q <sub>9</sub> pop2020 × subsidy	3.008 (1.64)
Q <sub>10</sub> pop2020 × policy	3.649 (1.35)	Q <sub>10</sub> pop2020 × subsidy	0.902 (0.58)
Constant	7.811*** (20.06)	Constant	7.322*** (17.01)
Observations	20,686	Observations	20,686
R-squared	0.286	R-squared	0.302
Number of cities groups	1,123	Number of cities groups	1,123
Year-month fixed effects	Yes	Year-month fixed effects	Yes
Cities groups fixed effects	Yes	Cities groups fixed effects	Yes

Notes:  $Q_i$ income2020( $i \in (2,10)$ ) is a series of dummy variables to show if the cities group belongs to the  $i$ -th decile of median disposable income. In column (1) the dependent variable is the dummy variable *policy*; In column (2) the dependent variable is a continuous variable *subsidy*. All regressions include year-month fixed effects and cities groups fixed effects. The independent variable is the value of the monthly carpooling volume per 1000 inhabitants. Standard errors are clustered at the cities group level. In parentheses are the robust t-statistics clustered at the cities group level. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%.