RIDING TOGETHER: ELICITING TRAVELERS' PREFERENCES FOR LONG-DISTANCE CARPOOLING*

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Abstract

Most seats in private cars are empty when drivers hit the road. Carpooling could thus represent a low-cost strategy to reduce carbon emissions in the transportation sector. Using revealed preference data from actual long-distance carpooling trips in France, we estimate passengers' preferences for the different characteristics of a ride. We find that passengers are highly price-elastic and value significantly the convenience of pick-up and drop-off locations. In contrast, their value of time once in the car is significantly lower than typical reference values. Finally, we discuss the effectiveness of a number of counterfactual policies aimed at promoting carpooling.

Keywords: revealed preferences, carpooling, long-distance transportation, value of time, sharing economy
JEL: L91, R41

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1 Introduction

The United States and the European Union host a fleet of about a quarter billion passenger cars each.[1] Twice their entire population could thus simultaneously sit in a private car. This impressive fleet of vehicles suggests a somewhat inefficient use of this capital: although the marginal cost of carrying an additional passenger is negligible, most cars on the road have only one or two occupants.[2] In other words, most seats in private cars are empty when drivers hit the road.[3]

Increasing the average occupancy rate of private cars through carpooling thus represents a very promising and cost-effective strategy to reduce carbon emissions from the transportation sector,[4] which are still on the rise (International Energy Agency, 2020). However, in contrast to ride-hailing applications, carpooling takes place in the private sphere: neither drivers nor passengers are professionals. Matching potential drivers and passengers is thus a big challenge. Carpooling indeed entails significant transaction costs, especially for one-time long-distance trips. To mention only a few examples, both parties have to trust each other, agree on pick-up and drop-off locations, pick a departure time, agree on a price, etc.

In the past two decades, technological innovations by digital platforms have considerably lowered these search and transaction costs, enabling the development of long-distance carpooling on a large scale. The online platform BlaBlaCar, which we study in this article, now gathers over 100 million users in 22 countries: every second, about 3 passengers start a trip they booked on the platform, with a mean traveled distance of 260 km.[5] Long-distance carpooling is in practice

[1]Sources: U.S. Bureau of Transportation Statistics for the United States, Eurostat for the European Union.

[2]In Europe for example, there are on average less than two persons per car on a given trip (BlaBlaCar and Le BIPE, 2019; Eurostat, 2021). In the data set we use in this work, we observe an average of about 1.5 persons per car in the absence of carpooling.

[3]In aggregate, the French government estimates that there are 50 million empty seats per day on the roads in France (`https://www.lemonde.fr/economie/article/2022/12/13/le-covoiturage-encourage-par-le-gouvernement_6154108_3234.html`, last accessed in December 2022).

[4]Of course, the environmental impact of carpooling is in theory ambiguous and depends on the choices drivers and passengers would have made in the absence of the possibility to carpool. Evidence from BlaBlaCar and Le BIPE (2019) suggests that the net short-run impact is a decrease in emissions even though more journeys are undertaken.

[5]https://blog.blablacar.com/newsroom/news-list/blablacar-reaches-100-million-members-for-its-15th-anniversary,

observed to double the average occupancy rate of private cars (BlaBlaCar and Le BIPE, 2019).[6]

Carpooling thus represents a cost-effective and readily available strategy to decrease carbon emissions in the transportation sector, one of the most important and difficult challenge in the fight against climate change. A series of ambitious measures to support carpooling are currently being rolled out in many countries (subsidies, dedicated infrastructure, etc., see Section 6 for more details). However, in the eyes of many travellers, engaging in carpooling still represents a major behavioral change relative to solo driving. To reach its full potential, carpooling thus needs to offer a service that matches passengers' preferences to the best extent possible. Understanding which trip characteristics matter most to travellers is critical to assess the expected efficiency of public policies. Will they encourage more users to carpool? Will they benefit passengers, drivers or both? The ambition of this article is to estimate a number of key parameters that determine the answers to these questions. Specifically, we estimate with unprecedented precision the preferences of passengers for the characteristics of carpooling rides. Knowing these preferences in turn enables us to assess the impact of a number of public policies, either currently implemented or under discussion.

Our study leverages very detailed and original revealed preference data. We study the actual choices made by passengers of BlaBlaCar, the largest carpooling platform in the world. The platform collects trip postings from drivers who have spare seats in their car. Drivers provide their departure time, origin and destination locations, requested price per seat as well as several other characteristics. Passengers can then browse trip listings on the website or on the app and book a seat on their preferred ride. We estimate discrete choice models to assess how passengers value the different characteristics of carpooling rides (price, duration, convenience of meeting points,

last accessed in December 2022.

[6]BlaBlaCar and Le BIPE (2019) estimate that occupancy rates of cars that offer carpool rides increase to 3.9 persons per car on average. In the dataset we use, which covers a period of one month in 2020,[7] occupancy rate only rises on average to 2.3 persons per car thanks to carpooling. This lower figure may be due to the impact of the Covid-19 pandemic on overall intercity travel demand.

etc.). Our empirical analysis focuses on France, BlaBlaCar's historical and largest market. We estimate our main model from actual bookings by over 10,000 passengers in 2020 for trips along 15 distinct corridors (defined as non-directed city pairs). Finally, we use our estimated model to run counterfactual scenarios.

Price endogeneity is obviously an important issue to consider in our setting. One may for example expect that successful drivers set their price differently than other drivers. Similarly, trip duration might be endogenous if unobserved confounders affect at the same time the duration and the expected utility from a ride. However, thanks to our access to proprietary data and extensive insights into the platform's institutional details, we are able to devise original instrumental strategies. These strategies exploit exogenous algorithm-driven variations and discontinuities in prices and durations which are invisible to the users of the platform.

We find that passengers are very sensitive to price, with a price elasticity higher than 5 (in absolute value). This value is large but consistent with the estimates found for other modes of transportation (see Section 2). In contrast, carpooling passengers are found to be somewhat insensitive to the time they spend in the car. We estimate an average value of travel time of around 3 €/hour. This value is much smaller than typical estimates in the transportation literature. It is however consistent the characteristics of long-distance carpooling. First, carpoolers are likely to have a higher marginal utility of income than the average population (see Section 3), which mechanically decreases their monetary value of travel time. Second, carpooling is often seen as a service of "soft" mobility where compressing time is not the main objective. Travelers may thus use this mode of transportation predominantly for trips for which they enjoy some flexibility.

Despite their low value of time, carpoolers are found to pay strong attention to the convenience of the pick-up/drop-off locations. Convenience, as measured by the distance (as the crow flies) between desired origin/destination and actual pick-up/drop-off points, is found to be the most useful characteristic in terms of predictive power.[8] We find that passengers would be willing to pay on average about 60cts to have a pick-up/drop-off point 1 kilometer closer to their desired origin/destination location. Assuming that the corresponding distance is traveled either by foot (say at 5 km/h) or by car (say at 50 km/h), the corresponding value of time lies between 3 and 30 €/hour, and is thus likely to be higher than the value of the time spent in the car. The convenience of pick-up and drop-off locations thus represents a large source of potential for efficiency gains in the context of carpooling. Meeting points can indeed be located anywhere in the public space, potentially offering a much better spatial coverage than any public transport system. As of today however, such meeting points are to a large extent chosen arbitrarily by drivers. We thus conclude that dedicating convenient and well-connected public spaces to carpooling, and/or encouraging drivers to pick convenient locations, could make a large difference.

Besides providing new estimates for key economic parameters (price elasticity, value of time, etc.) for an under-studied transportation segment (long-distance car travel), this article also contributes to the recent and growing literature on carpooling. It is indeed the first to leverage comprehensive revealed-preference data provided directly by an online platform, rather than relying on surveys or on scraped data. In particular we are able to devise original instrumental strategies, and to estimate with unprecedented accuracy the effect of previously-studied characteristics of carpooling trips, such as drivers' average rating. Our model also enables us to discuss the expected effect of several public policies designed to promote carpooling.

The rest of the paper is organized as follows. Section 2 further discusses the motivation for the present study and its contributions to the literature. Section 3 provides background information on carpooling in France and describes our data. Section 4 details our empirical strategy. Section 5 presents our main results. Section 6 explores the effectiveness of different policies that may impact the attractiveness of carpooling. Section 7 concludes.

[8]As measured by the increase in the log-likelihood function following the inclusion of the corresponging variable in the model being estimated.

2 Motivation and literature review

Among energy uses, transportation is the second largest source of greenhouse gases emissions after electricity and heat generation.[9] Global carbon emissions from transportation are still on the rise and primarily come from road transport, a sector whose biggest contributors in terms of aggregate emissions are private light and medium-duty vehicles. It is therefore critical to devise and implement mitigation strategies targeting private vehicles. A lot of attention in this area is directed to the switch towards electric mobility (Rapson and Muehlegger, 2022). However, converting the entire fleet of private cars to electric vehicles (EV) is a massive and very capital-intensive transition. It will therefore take many years, and the speed of this transition remains uncertain (Rapson and Bushnell, 2022). In the meantime, low-cost and readily-implementable policies can make a big difference.

Given the low average occupancy rate of private cars, promoting carpooling figures prominently among possible short-term public interventions. Because matching individual travelers entails significant search and transaction costs, carpooling was historically restricted to niche use cases, such a co-workers commuting together. However, digital platforms have recently considerably lowered these costs, paving the road to a large-scale adoption of carpooling.

In the transportation sector, digital platforms are most well-known in the context of ride-hailing. These platforms, such as Uber or Lyft, match professional drivers to passengers who choose their pick-up and drop-off locations. The corresponding trips tend to be short (a few kilometers) and to take place within cities. A recent but already pretty large literature studies these platforms from several perspectives, including passengers' preferences (Buchholz et al., 2020; Christensen and Osman, 2021; Goldszmidt et al., 2020), the value of drivers' work flexibility (Chen et al., 2019), passengers' benefits (Cohen et al., 2016), gender discrimination (Cook et al., 2021), pricing and the management of peak demand (Castillo et al., 2017) or payment methods (Alvarez and Argente,

[9] See for example `www.climatewatchdata.org`

2022).

Ride-hailing platforms however do not address the demand for medium and long-distance travel. Yet, although intercity car trips represent a small share of the total number of trips made in private cars, they represent a significant fraction of the total distance traveled, and thus of carbon emissions. In addition, comfort and convenience considerations when traveling long-distance trips may play an important role in car purchasing decisions, for example when choosing between internal combustion engine vehicles and EVs (Kempton, 2016). In contrast to ride-hailing applications however, carpooling platforms match occasional drivers and passengers. The external validity of insights derived from the ride-hailing literature in the context of carpooling is thus likely to be weak.

The literature on medium to long-distance carpooling is somewhat recent, and many research gaps remains. Existing studies have relied on surveys (Monchambert, 2020) or on scraped data (Farajallah et al., 2019; Lambin and Palikot, 2020; Yeung and Zhu, 2022). These studies focus on issues such as the impact of railway strikes (Yeung and Zhu, 2022), or the existence of discrimination (Farajallah et al., 2019; Lambin and Palikot, 2020). Revealed-preference studies put little emphasis on economic fundamental parameters (e.g. passengers' price elasticity or value of time), in parts because of data limitations (e.g. difficulty to construct a credible instrument for prices). This article contributes to this literature by being the first to leverage comprehensive revealed-preference data provided directly by an online platform. Importantly, we are able to implement original instrumental strategies to credibly estimate passengers' preferences for the main characteristics of carpooling rides.

Knowledge of these preferences in turn allows us to contribute to broader research areas. First, this work connects to a vast literature on estimating passengers' price elasticity for different modes of transportation. We find a large price elasticity relative to most existing estimates. Alternative modes of transportation to private cars, such as trains or buses, are indeed typically characterized by a price elasticity lower than 1 (see e.g. Wardman, 2014 for a meta-analysis). The range of price elasticity estimates for car trips is very wide, and highly dependent on the use case of interest. For example, Alvarez and Argente (2020) find an absolute elasticity lower than 1.5 for short distance ride-hailing in Mexico, and Cohen et al. (2016) an absolute elasticity below 0.6 in large U.S. cities. In contrast, other studies find much larger elasticities, such as 2 to 8 in Buchholz et al., 2020 (for the Czech Republic), or 6 to 10 in Christensen and Osman, 2021 (for Egypt). Consistently with our results, Yeung and Zhu (2022) estimate a price-elasticity between 3 and 11 for long-distance carpooling.[10]

Second, a large body of work discusses the value of travel time, both theoretically (Becker, 1965) and empirically (Small, 2012). The value of time is indeed a key input to most cost-benefit analyses of transportation infrastructures, as time savings can represent up to 60-80% of the expected benefits of a project (Hensher, 2001; Shires and De Jong, 2009). Therefore, impact assessments are very sensitive to the assumed value of time of users (Welch and Williams, 1997). We contribute to this literature by providing a new estimate for an original setting, namely long-distance carpooling in France. Our estimate of 3 €/hour is much smaller than the values typically found in the transportation literature, including the reference value recommended for leisure car trips in France (about 11 €/hour for a 300 km trip (Quinet, 2013)). Excluding studies based on stated preferences,[11] estimates for the value of time for long-distance travel range from as high as the shadow wage (Becker, 1965) to as low as 6 €/hour (Abrantes and Wardman, 2011). Our estimate is also lower than the ones found in the literature on ride-hailing (e.g. 13 €/hour in Buchholz et al., 2020). The composition of the population of carpoolers may explain some of the differences between carpooling and other modes of transportation (see Section 3). In addition, carpooling is typically perceived as less punctual than other modes of transportation, and may therefore be

[10]Their study is however based on scraped data and focuses on the specific period of railway strikes, when price elasticity may be expected to be smaller than usual.

[11]Abrantes and Wardman (2011) and Daly et al. (2014) suggest that stated-preference estimates may over-estimate the value of time by as much as 20 to 40%.

predominantly used for flexible trips.

We next discuss the setting of our study and provide a descriptive analysis of our data.

3 Data

3.1 Background

We rely on detailed data from BlaBlaCar, the largest carpooling platform in the world. The company operates in 22 countries and has over 100 million registered users. Both drivers and passengers are all private individuals who use the platform occasionally, professional use of the platform being prohibited. Registration to the platform is free of charge and mandatory to post or book a trip.[12] In contrast to carpooling in the context of daily commutes, a typical trip on the platform is an occasional long-distance intercity travel where the driver and the passenger(s) do not know each other and are unlikely to meet again in the future.

Schematically, the platform matches drivers and passengers in two steps.[13] It first builds an inventory of possible trips from drivers' postings. At any time, drivers can log in the platform and enter information about an upcoming trip for which they have spare seats in their car. The trip characteristics they must fill in are the pick-up and drop-off locations, the departure time, possible intermediate stopovers where passengers may be picked-up/dropped-off, the price per seat, the number of available seats, and whether booking requests will be accepted automatically or manually. Prospective passengers can then make search requests by entering their desired departure date, origin and destination. The platform returns them the list of possible rides for the received request. Importantly, and in contrast to many other digital platforms, the search ranking in BlaBlaCar follows a very simple rule: all the available rides for the requested day are ordered chronologically by departure time. The ranking thus does not convey any information about the

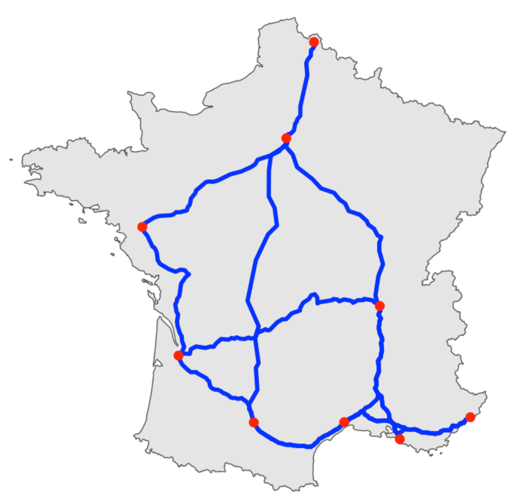
[12] All users fill in a public profile their with name and age, and possibly their picture and a short bio. New drivers receive a registration subsidy, in the form of a gasoline coupon worth 15€ upon the completion of their first trip.

[13] Appendix A provides more detail on how drivers and passengers are matched through the platform.

relevance or the quality of each ride. A number of ride characteristics appear directly on the page that displays search results, and are thus very salient to prospective passengers: (i) the price of the ride; (ii) its duration (departure time and arrival time); (iii) the meeting points for pick-up and drop-off, along with their proximity (less than 3 km away, between 3 and 15 km away and more than 15 km away); (iv) information on the driver (average rating, first name, picture); (v) whether booking is automatic or requires a manual approval by the driver; and (vi) whether the driver has committed to leave the middle backseat empty. By clicking on a particular ride, passengers can further learn (vii) the exact addresses for pick-up/drop-off along with the distance between these locations and the origin/destination addresses entered by the passenger (in km); (viii) whether the requested origin and destination cities are also those of the driver or instead stopovers along his trip ; (ix) further information on the driver (number of ratings, preferences regarding smoking and pets, car model, etc.).

Passengers can finally select a ride and send a booking request to the corresponding driver. If the request is accepted, the match is confirmed and contact information are shared to the driver and the passenger (respective phone numbers). Once the trip has taken place, both users are invited to rate their experience using a five star rating system.

Figure 1: Corridors where the trips in our dataset took place



The present study focuses on France where BlaBlaCar was founded in 2006 and which is one of the platform's largest market with 20 million registered users (30% of the population of the country). Our analysis uses data on 10,114 bookings for trips that took place over the study period. Figure 1 shows the 15 corridors (defined as non-directed city pairs) along which these trips were made. These corridors were selected for two main reasons. First, a large number of trips are observed along these axes. Second, the platform also operates buses on theses corridors. Because (i) buses are displayed along with carpooling rides in search results, and (ii) we observe whether prospective passengers chose to book a carpool or a bus seat, we use the bus as the outside option in our discrete choice models.[14] Regarding the period of time when trips took place, the choice of study period was driven by its suitability for implementing our empirical strategy. In particular, our instrumental variable for prices leverages a feature of the platform that was introduced only in 2018, and the quality of some detailed information we use in robustness checks increased significantly towards the late 2010s. In addition, we chose a month during which Covid-19 restrictions in France, while still present, were much less severe as they were during the initial lock-down of March 2020. Finally, we were able to check with the platform that they were not conducting any large-scale experiment on our axes of interest in this specific month.

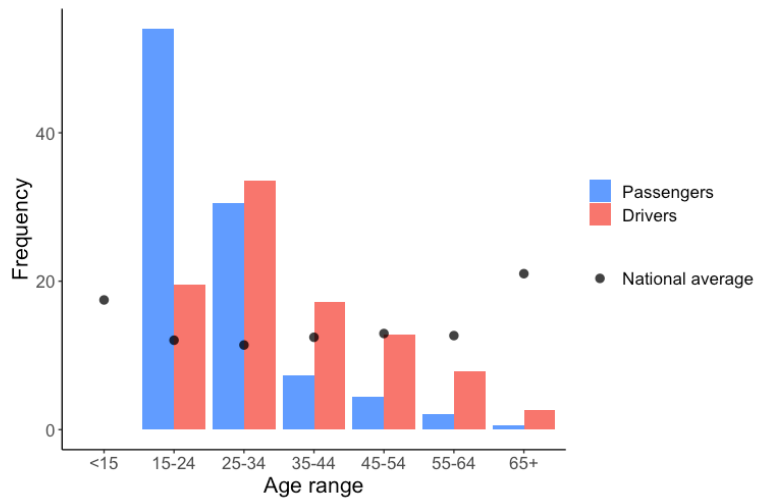
3.2 Characteristics of the sample population

Figure 2 displays the age distribution of the users we observe in our dataset. Reflecting the relative popularity of the platform among younger populations, more than half of the passengers are between 18 and 24 years old. Drivers tend to be a bit older, with 25-34 year olds being the most represented age range.[15]

[14] Appendix E shows that our results do not appear to be particularly sensitive to this choice of outside option.

[15] Registration on BlaBlaCar is restricted to users aged 18 or more. For privacy-preserving reasons, we do not observe the gender of users. Chapelle et al. (2023) estimates, based on scraped and experimental data, that drivers are predominantly male (70%), while the population of passengers is fairly balanced (44% male).

Figure 2: Distribution of the age of passengers (blue bars) and drivers (red bars) in our dataset. Black dots are national statistics from INSEE. Frequencies are given in percents.



Besides providing their age, platform users are invited to fill in a profile with stated horizontal preferences: whether they like to chat and/or listen to some music in the car, whether they smoke and whether they like or allow pets. Table 1 shows these stated horizontal preferences over our sample population. Note that filling in this information is optional for users and is only displayed in their profile if they have done so. A default value of "maybe" is otherwise stored in the platform's database.

Table 1: Horizontal preferences of users in our dataset, as stated in their public profile

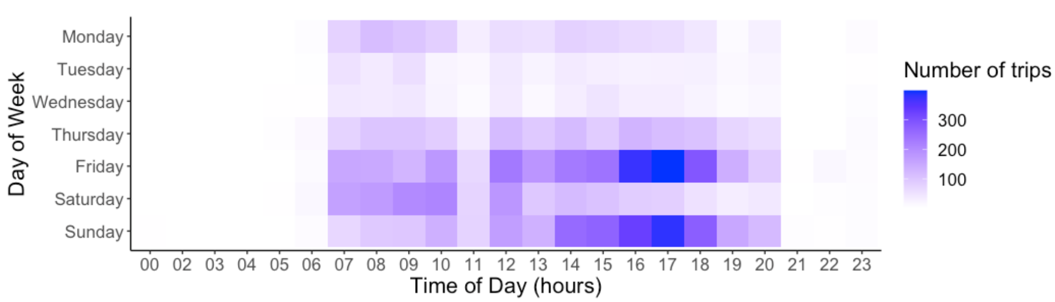
Share of	Passengers			Drivers		
(%)	yes	no	maybe	yes	no	maybe
Chattiness	12.8	2.8	82.5	22.8	2.5	74.6
Music	50.7	0.3	47.1	66.7	0.6	32.7
Pets	19.5	17.8	60.8	16.3	42.3	41.4
Smoking	16.4	26.2	55.5	10.7	56.5	32.7

Table 1 suggests that drivers fill in horizontal preference information more often than passengers. This observation is consistent with the fact that it is much easier for passengers than for drivers to select the persons with whom they travel. Music preferences are filled in by most users, almost exclusively to signal a preference for listening to some music in the car. Attitude towards smoking is the second most frequent information to be provided, most often to indicate a preference for non-smokers, especially so for drivers. While passengers are equally likely to declare liking or disliking travelling with pets, an overwhelming majority of drivers prefer not to do so. Finally, most users do not bother entering their self-assessed level of chattiness.

3.3 Characteristics of trips

Figure 3 shows the heatmap of the number of trips taken by passengers, broken down by day and hour of departure. Most trips took place on Friday and Sunday evenings, meeting a demand for travel when people take a weekend away from home. In contrast, very few trips depart at night. Therefore, our model will make a distinction between three time periods (see Section 4): day time (7am to 9pm), night time (9pm to 7am) and peak hours (4-9pm on Fridays and Sundays).

Figure 3: Heatmap of the number of observed trips by day and hour of departure



From the perspective of passengers, a carpool ride may be seen as a bundle of characteristics. Table 2 provides summary statistics for the characteristics of offered rides.[16] We observe a total of 43,553 unique offered carpool rides. Their price and duration vary significantly both within and across routes. About 10% of rides are offered by first-time drivers, and the average rating of drivers

[16]These statistics only keep a single instance of duplicates, that is of rides that appear in the choice set of several passengers. On average, a given ride appears in 2.6 choice sets. The distribution is however skewed to the right due to hours of peak demand (with many passengers) and heterogeneous lags between the date at which a ride is posted and the corresponding departure date.

who have already completed trips on the platform is homogeneous across routes at 4.7 (out of 5). Most drivers (85%) choose to leave the middle back seat empty, and 75% set manual approval of booking requests.[17]

Table 2: Summary statistics for the main trip characteristics that only depend on the ride. Standard deviations are given in parenthesis for non-binary variables.

Route	N rides	Price (€/seat)	Duration (hours)	Distance (km)	New drivers (%)	Driver rating	Automatic booking (%)	Two max back (%)
Bordeaux-Lyon	559	33.5 (5.9)	5.8 (0.5)	544 (39)	11	4.7 (0.4)	17	83
Bordeaux-Nantes	4817	21.4 (3.6)	3.6 (0.2)	350 (13)	7	4.7 (0.3)	25	90
Bordeaux-Toulouse	6106	14.9 (2.6)	2.6 (0.2)	243 (9)	8	4.7 (0.3)	25	88
Lille-Paris	4732	14.7 (2.6)	2.5 (0.2)	218 (11)	9	4.6 (0.3)	37	80
Lyon-Marseille	2814	20.6 (4.1)	3.3 (0.3)	306 (19)	12	4.7 (0.3)	19	85
Lyon-Montpellier	2932	19.7 (3.5)	3.3 (0.2)	299 (12)	9	4.7 (0.3)	21	85
Lyon-Nice	1336	30.7 (5.1)	4.9 (0.4)	454 (27)	9	4.7 (0.3)	20	81
Lyon-Paris	2827	29.2 (5.6)	4.8 (0.3)	462 (19)	12	4.7 (0.3)	26	85
Marseille-Montpellier	1975	10.9 (2.2)	2.0 (0.2)	166 (10)	7	4.7 (0.2)	23	81
Marseille-Nice	2743	11.9 (2.4)	2.0 (0.3)	171 (19)	9	4.7 (0.2)	18	83
Marseille-Toulouse	1376	25.7 (4.6)	4.3 (0.4)	396 (23)	8	4.7 (0.3)	19	85
Montpellier-Nice	934	21.1 (3.8)	3.5 (0.4)	311 (23)	10	4.7 (0.2)	18	85
Montpellier-Toulouse	6578	15.2 (2.7)	2.6 (0.2)	239 (9)	8	4.7 (0.2)	20	86
Nantes-Paris	2647	24.5 (4.0)	4.0 (0.3)	376 (17)	8	4.6 (0.3)	37	87
Paris-Toulouse	1177	39.4 (6.9)	7.0 (0.5)	668 (34)	11	4.7 (0.3)	31	83
Total/Mean	43553	19.3	3.2	301.7	8.9	4.7	24.8	85.2

3.4 Spatial match between drivers and passengers

We organize the data so as to take the perspective of passengers when they made their booking decision.[18] In other words, we gather a collection of "choice situations" using very detailed information from the platform. First, we observe the search requests made by passengers: desired date of departure, GPS coordinates of desired origin and destination.[19] Second, we know precisely the choice set that passengers were facing when they booked their ride.

Passengers enter precise addresses for their desired origin and destination.[20] However, drivers

[17] All booking requests involving stopovers suggested by the platform rather than by drivers themselves, which we detail below, require manual approval (see Section 4).

[18] Appendix B provides more details about the construction of our final dataset.

[19] For confidentiality reasons, some noise has been added to GPS coordinates so that the GPS locations listed in our dataset are within a radius of 1 km of actual coordinates. Our discrete choice model however uses as an explanatory variable the Euclidean distance between passengers' origin/destination (as stated in their search request) and drivers' pick-up/drop-off locations. These distances where computed using the exact GPS locations.

[20] The platform does not require passengers to enter a precise address: they may instead simply enter their desired cities of origin and destination. As explained in Appendix B, we however restrict attention to passengers who did enter a precise address for both their origin and destination.

may offer pick-up and drop-off locations that do not perfectly correspond to the passengers' requests. The choice set of a given passenger thus consists of carpooling rides with pick-up (resp. drop-off) locations more or less distant from the desired origin (resp. destination). Table 3 reports the mean and standard deviation of the distribution of the minimum and average distance between passengers' desired origin (destination) and the pick-up (drop-off) locations of the carpooling rides in their choice set. Passengers can on average find a ride within 1 or 2 kilometers of their desired origin/destination, but the quality of the spatial match between passengers and drivers is very heterogeneous.

Table 3: Summary statistics (mean and standard deviation) for the minimum and mean distance between desired origin/destination and the pick-up/drop-off locations available in passengers' choice sets.

Route	N passengers	Min distance orig. pick-up (km)	Mean distance orig. pick-up (km)	Min distance dest. drop-off (km)	Mean distance dest. drop-off (km)
Bordeaux-Lyon	185	1.6 (1.8)	7.7 (4.2)	1.5 (1.6)	8.0 (4.5)
Bordeaux-Nantes	1255	1.2 (1.1)	5.5 (1.5)	1.1 (1.2)	5.3 (1.7)
Bordeaux-Toulouse	1216	1.0 (1.2)	4.7 (1.6)	0.9 (1.2)	4.7 (1.6)
Lille-Paris	1954	1.2 (1.6)	4.7 (2.8)	1.2 (1.7)	4.5 (2.8)
Lyon-Marseille	402	0.8 (1.4)	6.5 (4.4)	0.7 (1.2)	6.0 (3.9)
Lyon-Montpellier	483	0.9 (1.4)	4.4 (2.1)	0.9 (1.5)	4.3 (2.5)
Lyon-Nice	329	1.5 (2.1)	7.1 (3.9)	1.5 (1.8)	7.0 (4.1)
Lyon-Paris	403	1.4 (1.7)	7.6 (3.2)	1.3 (1.8)	6.9 (3.3)
Marseille-Montpellier	565	0.8 (1.0)	3.0 (1.6)	0.8 (1.1)	3.0 (1.7)
Marseille-Nice	1026	0.9 (1.5)	5.1 (3.0)	0.9 (1.5)	4.8 (2.7)
Marseille-Toulouse	296	1.1 (1.6)	7.8 (4.7)	1.1 (1.8)	8.2 (4.7)
Montpellier-Nice	242	2.0 (2.5)	6.8 (4.1)	1.9 (2.4)	6.9 (4.4)
Montpellier-Toulouse	809	0.8 (1.0)	4.1 (1.5)	0.8 (1.1)	4.0 (1.6)
Nantes-Paris	680	1.9 (2.2)	8.1 (4.2)	1.7 (2.0)	7.5 (3.8)
Paris-Toulouse	269	2.0 (3.2)	10.2 (5.3)	1.8 (2.8)	9.9 (5.8)
Total/Mean	10114	1.1	5.5	1.1	5.3

For any given choice set, passengers book either a carpooling ride or a bus seat. The market share of carpooling rides (vs. bus seats) varies across routes, from less than 50% to over 80%. We observe no obvious correlation between the market share of carpooling and the route distance or the ratio between the number of passengers and the number of available rides. However, higher bus frequencies are – somewhat intuitively – associated with a higher bus market share.

4 Empirical strategy

4.1 Explanatory variables

We assume that the utility that a passenger derives from a given ride primarily depends on the characteristics of this ride. Table 4 lists the main characteristics included in our models. We further add a set of variables capturing how similar the driver is to the passenger in terms of age range and declared horizontal preferences (see Section 3).

Table 4: Main explanatory variables used in our models

Variable name	Meaning and unit
price_passenger	price of a seat (in €/seat)
duration_hours	displayed duration for the ride (in hours)
from_distance	Euclidean distance between origin and pick-up (in km)
to_distance	Euclidean distance between destination and drop-off (in km)
driver_rating	average rating (out of 5) of the driver (set to average rating for new drivers)
is_new_driver	dummy variable taking the value 1 if the driver is new to the platform
is_booking_auto	dummy variable taking the value 1 if booking confirmation is automatic
is_two_max_back	dummy variable taking the value 1 if middle back seat is left empty
starts_before	dummy variable taking the value 1 if the driver has a different origin city
continues_after	dummy variable taking the value 1 if the driver has a different destination city

Before detailing our model specifications, we discuss how we address possible endogeneity concerns about the price and duration of carpooling rides.

4.2 Instrumental variables

Carpool prices

Observed prices are likely to be endogenous. Price setting is indeed decentralized and drivers are free to set their own price for a seat in their car. As a result, posted prices may be correlated with unobservable characteristics of drivers or of market conditions.[21] In addition, the platform nudges drivers to price their seats proportionally to the distance of the trip because carpoolers are supposed (and legally obliged) to only share the costs of the trip, as opposed to making a profit.

[21] Note however that fuel prices were very stable over our period of interest (see Appendix C).

As an illustration, Table 5 shows the obtained estimates when regressing the price of a ride (excluding rides generated by the platform itself, see below) on route fixed effects and a number of ride characteristics. We observe that drivers with a higher rating, who accept booking requests automatically and who leave the middle back seat empty tend to set lower prices for their rides. In other words, several desirable features of rides are correlated with lower prices. A possible concern is thus for example that drivers who are most popular for reasons we do not observe (e.g. because they wrote down an appealing short bio) also set lower prices than the average driver.

Table 5: Regression of the price of a ride (excluding rides added by the platform itself) on other characteristics and route fixed effects.

	Dependent variable:
	price_passenger
driver_rating_average	−0.230 (0.064)
is_new_driver	−0.594 (0.062)
is_booking_auto_accept	−0.382 (0.034)
is_two_max_back	−1.040 (0.045)
starts_before	0.158 (0.035)
continues_after	0.218 (0.034)
Route FE	yes
Observations	35,427
R^2	0.814

To instrument for prices, we exploit a platform-specific source of exogenous variation. In order to increase both spatial coverage and the number of ride options, the platform generates (using an algorithm) and displays rides that correspond to subsets of existing trips, even if drivers did not explicitly indicated their willingness to stop at the corresponding pick-up and/or drop-off locations. We call such rides "smart stopovers". Passengers can then book any regular or smart stopover ride, the latter requiring a manual approval by the driver. Smart stopovers have two important characteristics that make them appealing to use them as price instruments. First, a prospective passenger cannot tell regular rides apart from smart stopover rides. Both are displayed in exactly the same fashion, and chances are that the vast majority of passengers were not even aware of the existence of smart stopovers. Second, in order to increase subsequent acceptance rates by drivers (who get unexpected requests for sub-trips they did not post themselves), the platform exogenously increase the per-km price of smart stopover trips by $\sim$5-20% (relative to the per-km price of driver's actual trip). As a result, we use a set $\{\mathbf{1}_{r,st}\}_r$ of price instruments, defined as dummy variables that take the value 1 if a given trip is along route r and is a smart stopover ride.

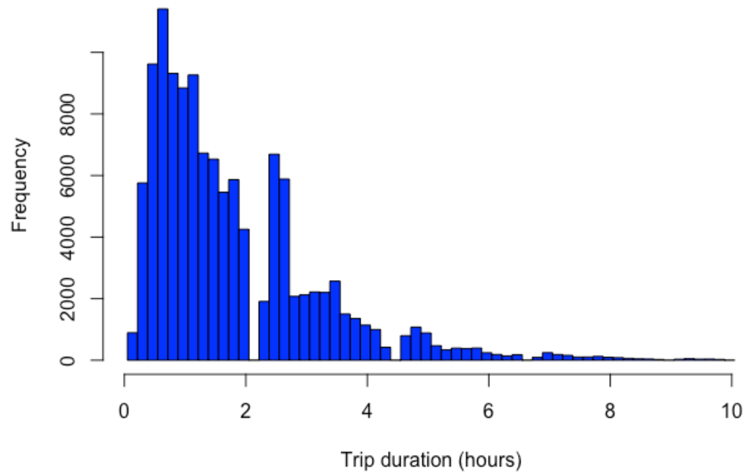
Displayed duration of a ride

Drivers do not choose the trip duration displayed to prospective passengers. Duration is instead computed by the platform by performing the routing between the pick-up and drop-off locations. Besides the heterogeneity in the exact GPS locations of pick-up and drop-off locations, displayed duration vary across rides within a given route for two main reasons.

First, if a driver indicated that he is willing to stop at one or several cities along his way, the routing algorithm will consider that the driver will make all the corresponding detours. In practice however, the driver will only have to make such detours if there is an actual passenger booking a trip from/to the corresponding stopover. We thus use as our first instrument for duration the number nb_stops of stops between pick-up and drop-off locations where the driver has indicated being willing to stop at. Importantly, such cities are not displayed to prospective passengers when they browse the list of possible rides. Passengers thus have no easy way to infer that differences in displayed duration within a given choice set are driven in parts by these declared possible stopovers.

Second, because the French Road Safety Interministerial Delegation encourages to take a break every two hours when driving, the platform exogenously assumes that drivers will take a 15-20 min rest break on any sub-segment of their trip that lasts more than 2 hours. Figure 4 illustrates this observation. It shows the histogram of the assumed duration of each sub-trip listed in the inventory of trips. If a driver travels from A to D and has declared stopping by B and C, then the correspond-

Figure 4: Histogram of the duration –as computed by the platform – of all sub-trips observed in our final dataset.



ing sub-trips are A-B, B-C and C-D. One can see that the distribution exhibits "gaps" at 2 hours, 4 hours and 20 min, and so on. For each ride, the number of rest breaks, denoted nb_exo_breaks, is used as an additional instrument for duration. Again, there is no easy way for passengers to know whether and how these rather arbitrary breaks are computed and factored into the displayed duration.

First-stage results

Table 6 reports the result of the first stage. We observe that our instruments have the expected impact on the two variables that we treat as endogenous (price and duration).

We make two observations. First, smart stopover rides exhibit higher prices than regular rides, with a mark-up that increases (in absolute value) with the route distance. They are found to be about 10% more expensive than regular rides. Second, an additional stopover and an additional exogenous break induce respectively into a 11-minute increase (0.190×60) and a 15-minute increase (0.244×60) in the duration of the ride. Finally, F-statistics suggest that our instruments have a strong explanatory power on the endogenous variables.

Table 6: First stage results (exogenous variables other than the instruments are omitted in the Table for more clarity).

	Price (alone) (1)	Price (both) (2)	Duration (alone) (3)	Duration (both) (4)
nb_stops		0.164 (0.020)	0.196 (0.001)	0.190 (0.001)
nb_exo_breaks		0.471 (0.037)	0.245 (0.002)	0.244 (0.002)
is_smart_stopover:routeBordeaux-Lyon	3.300 (0.266)	3.178 (0.266)		−0.017 (0.016)
is_smart_stopover:routeBordeaux-Nantes	2.926 (0.083)	2.909 (0.083)		0.098 (0.005)
is_smart_stopover:routeBordeaux-Toulouse	1.561 (0.076)	1.537 (0.076)		−0.019 (0.005)
is_smart_stopover:routeLille-Paris	1.135 (0.078)	1.144 (0.078)		−0.156 (0.005)
is_smart_stopover:routeLyon-Marseille	2.325 (0.117)	2.338 (0.117)		−0.083 (0.007)
is_smart_stopover:routeLyon-Montpellier	2.384 (0.108)	2.379 (0.108)		−0.030 (0.006)
is_smart_stopover:routeLyon-Nice	2.043 (0.169)	1.988 (0.169)		−0.221 (0.010)
is_smart_stopover:routeLyon-Paris	3.348 (0.114)	3.248 (0.114)		−0.070 (0.007)
is_smart_stopover:routeMarseille-Montpellier	1.180 (0.133)	1.237 (0.133)		0.022 (0.008)
is_smart_stopover:routeMarseille-Nice	0.258 (0.099)	0.334 (0.100)		−0.131 (0.006)
is_smart_stopover:routeMarseille-Toulouse	3.093 (0.168)	3.132 (0.168)		−0.069 (0.010)
is_smart_stopover:routeMontpellier-Nice	1.721 (0.199)	1.706 (0.199)		−0.120 (0.012)
is_smart_stopover:routeMontpellier-Toulouse	1.624 (0.070)	1.604 (0.070)		−0.128 (0.004)
is_smart_stopover:routeNantes-Paris	2.547 (0.119)	2.537 (0.119)		0.040 (0.007)
is_smart_stopover:routeParis-Toulouse	5.554 (0.199)	5.451 (0.199)		−0.030 (0.012)
F statistic	274	251	5105	895
Observations	61,404	61,404	61,404	61,404
R^2	0.790	0.790	0.964	0.966

4.3 Model

We estimate a logit model with the following specification:

$$U_i(j) \equiv \beta^T.X_{ij} + \xi_{m,j\neq 0} + \epsilon_{ij} \tag{1}$$

In Equation 1, i indexes passengers, j indexes drivers ($j = 0$ for the bus outside option), m indexes markets, which we define as pairs of a given route and a given time period (day, night or peak hours). X_{ij} are the characteristics of the ride.[22] They include the variables described in Table 4, matching dummies between drivers' and passengers' characteristics and, for instrumented specifications, the residuals from the first stage. $\xi_{m,j\neq 0}$ aims to capture any intrinsic preference for carpooling over taking the bus. Given our definition of markets, the intrinsic preference for carpooling over the bus is allowed to vary by route and time periods. The error term ϵ_{ij} is assumed to be i.i.d. extreme value distributed.

[22]These variables are set to zero for the bus outside option as we do not observe the characteristics of bus rides at the time of booking.

In what follows we report five model specifications. The first three are conditional logits with fixed coefficients. Specification (1) neither instruments for price nor for duration, specification (2) instruments for price only and specification (3) instruments for both price and duration. The last two specifications fit normal distributions for the price and duration coefficients (random coefficient logit). Specification (4) only instruments for price, while specification (5) instruments for both price and duration. Specification (5) is our preferred model.

5 Results

5.1 Main estimates

Table 7 reports our main results. First, we note that instrumenting for prices was warranted. The instrumented coefficient is twice as large as the non-instrumented coefficient, which is consistent with our concern that lower prices may be correlated with unobserved desirable features of the rides. Second, the necessity of considering duration as endogenous is less clear cut: first-stage residuals are not significant at the 1% level and instrumenting duration has a smaller impact on the point estimate of the corresponding coefficient. Third, the random coefficient logit specifications (4 and 5) suggest a high degree of heterogeneity among passengers regarding their sensitivity to price and duration. Fourth, the coefficients capturing the sensitivity to the quality of the spatial match (from_distance and to_distance) are the most precisely estimated and have the highest explanatory power among all variables.[23] Finally, the coefficients for all other variables have the expected signs, except for the variable is_two_max_back which is negative while this variable is meant to signal a rather comfortable trip. The corresponding coefficient is however only weakly significant (and sometimes not significant) at standard levels.

In what follows, we use estimates from specification 5, which is our preferred specification.

[23] As measured by the increase in the log-likelihood of the model subsequent to their inclusion.

Table 7: Obtained estimates for our five specifications

	Dependent variable:				
	choice				
	Logit	Logit	Logit	RC logit	RC logit
	(1)	(2)	(3)	(4)	(5)
price_passenger	−0.167 (0.005)	−0.302 (0.020)	−0.267 (0.019)	−0.355 (0.022)	−0.317 (0.021)
duration_hours	−0.562 (0.066)	−0.590 (0.066)	−0.674 (0.103)	−1.066 (0.085)	−1.135 (0.123)
from_distance	−0.165 (0.005)	−0.169 (0.005)	−0.168 (0.005)	−0.200 (0.005)	−0.198 (0.005)
to_distance	−0.134 (0.004)	−0.137 (0.004)	−0.136 (0.004)	−0.167 (0.004)	−0.166 (0.004)
is_new_driver	−0.349 (0.057)	−0.425 (0.058)	−0.405 (0.058)	−0.468 (0.061)	−0.445 (0.061)
driver_rating_average	0.395 (0.058)	0.395 (0.058)	0.395 (0.058)	0.418 (0.063)	0.417 (0.063)
is_booking_auto_accept	0.283 (0.030)	0.170 (0.034)	0.198 (0.033)	0.174 (0.035)	0.205 (0.035)
is_two_max_back	0.027 (0.039)	−0.093 (0.043)	−0.065 (0.043)	−0.118 (0.044)	−0.087 (0.044)
starts_before	−0.316 (0.031)	−0.277 (0.032)	−0.296 (0.033)	−0.310 (0.033)	−0.328 (0.035)
continues_after	−0.420 (0.031)	−0.366 (0.032)	−0.387 (0.033)	−0.354 (0.033)	−0.375 (0.034)
match_chattiness_yes	−0.030 (0.085)	−0.040 (0.085)	−0.036 (0.085)	−0.076 (0.090)	−0.071 (0.090)
match_music_yes	0.214 (0.037)	0.205 (0.037)	0.207 (0.037)	0.176 (0.040)	0.179 (0.040)
match_pets_yes	0.098 (0.077)	0.019 (0.078)	0.039 (0.078)	0.042 (0.082)	0.064 (0.082)
match_smoking_yes	0.171 (0.099)	0.210 (0.099)	0.199 (0.099)	0.236 (0.102)	0.225 (0.102)
match_smoking_no	0.219 (0.046)	0.221 (0.046)	0.220 (0.046)	0.200 (0.052)	0.199 (0.052)
match_age	0.161 (0.031)	0.138 (0.031)	0.144 (0.031)	0.124 (0.033)	0.130 (0.033)
is_carpool:departnight	−2.002 (0.140)	−1.965 (0.140)	−1.976 (0.140)	−2.032 (0.189)	−2.041 (0.189)
is_carpool:departpeak	0.873 (0.040)	0.920 (0.040)	0.909 (0.040)	0.990 (0.048)	0.976 (0.048)
price_only_residuals		0.141 (0.021)		0.173 (0.021)	
price_both_residuals			0.105 (0.020)		0.134 (0.020)
duration_both_residuals			0.198 (0.130)		0.189 (0.144)
sd.price_passenger				0.035 (0.020)	0.032 (0.021)
sd.duration_hours				0.863 (0.060)	0.863 (0.060)
Market Fixed Effects	yes	yes	yes	yes	yes
Price Instrument	no	yes	yes	yes	yes
Duration Instrument	no	no	yes	no	yes
Observations	10,114	10,114	10,114	10,114	10,114
Log Likelihood	−18,798.740	−18,773.920	−18,782.460	−18,607.090	−18,617.650

Note: p<0.1; p<0.05; p<0.01

5.2 Interpretation

From the logit formula for the probability of choosing a given alternative j, one can show that the elasticity with respect to a characteristic x is given by:

$$-\beta_x(1 - \mathrm{Pr}_j) * x_j \tag{2}$$

where Pr_j is the estimated probability that the passenger will choose alternative j. Table 8 reports summary statistics for the distributions of the implied elasticities with respect to the price, duration and distance to pick-up/location of carpool rides.

Table 8: Distribution of implied price, duration and distance to pick-up/location elasticities (using specification 5).

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Elasticity_price_passenger	153,718	5.54	2.06	0.05	4.07	6.48	24.07
Elasticity_duration_hours	153,718	3.30	1.04	0.04	2.71	3.83	10.77
Elasticity_from_distance	153,718	1.04	0.93	0.00	0.46	1.35	9.91
Elasticity_to_distance	153,718	0.84	0.76	0.00	0.36	1.09	8.30

Passengers are found to be highly price elastic, with a mean elasticity higher than 5. Although the elasticity with respect to duration is also found to be high, the underlying within-route variation in ride duration is much smaller than price variations (see Table 2). Therefore, duration is in practice much less instrumental in driving passengers' choices than price. Finally, although the elasticities with respect to the distance to pick-up and to drop-off locations are found to be lower than for price and duration, these variables are actually the ones with the highest explanatory power due to the large heterogeneity in the quality of the spatial match between drivers and passengers.

Another way to interpret our results is to derive the implied trade-offs between characteristics. Indeed, if two characteristics (x_1, x_2) have respected (estimated) coefficients $(\hat{\beta}_1, \hat{\beta}_2)$, then a change (dx_1, dx_2) in characteristics leaves the passenger indifferent if:

$$dU = 0 = \hat{\beta}_1 dx_1 + \hat{\beta}_2 dx_2 \tag{3}$$

The ratio $\frac{\hat{\beta}_2}{\hat{\beta}_1}$ then captures by how much x_1 should increase to compensate for a decrease of $-dx_2$ in characteristic 2. If characteristic 1 is the price of the ride, this compensation is expressed in money terms and thus directly interpretable.

Using this approach, we estimate the value of time of passengers to be about 3 €/hour. This value is significantly lower than typical estimates from the literature, as well as from public reference values for cost-benefit analyses. Our result may be rationalized in several ways. First, the population of carpoolers is biased towards users with a higher marginal utility of income than average (e.g. students). Second, carpooling mainly meets a demand for leisure trips (as opposed to business trips), for which passengers tend to be more flexible. Nonetheless, the users of BlaBlaCar platform in France represent a very sizable fraction of the population (20 million registered users) and a large number of trips. The fact that a sizeable segment of demand for long-distance travel is from passengers with a low value of time can thus have a number of policy implications.

Finally, the value of convenience, which we define as the willingness-to-pay for having pick-up or drop-off locations closer to the desired origin and destination, is estimated to be about 0.6 €/km. Assuming that the corresponding distance is traveled either by foot (say at 5 km/h) or by car (say at 50 km/h), the corresponding value of time lies between 3 and 30 €/hour. In other words, the value of time for the first and last miles is found to be higher than the value of time spent in the car. The value of convenience can also be usefully compared to the price of a ride-hailing service. On average, passengers have to travel 3.2 km between their desired origin/destination locations and their actual pick-up/drop-off points. The utility loss incurred by passengers due to this inconvenience may estimated at 1.9 euros (3.8 euros in total). This is significantly lower than the average price of 5.3 euros for a 3.2-km trip with a ride-hailing service, which suggests that passengers are unlikely to consider these services in practice.[24]

5.3 Heterogeneity analysis

In our model specifications, the term $\xi_{m,j\neq0}$ captures any intrinsic preference for carpooling over taking the bus. This intercept is market-specific, where a market is defined as the combination of an axis and a departure period (day, night or peak hours). In other words, we allow the substitution between carpooling and buses to be to some extent market-specific.[25]

From the logit formula for the probability of choosing a given alternative k, the cross-elasticity of the demand for taking the bus with respect to a characteristic x of a carpooling trip is given by:

$$-\beta_x x_k \mathrm{Pr}_{j=0} \tag{4}$$

where $\mathrm{Pr}_{j=0}$ is the predicted probability to choose the bus alternative. We can therefore compute, for each carpooling ride that has appeared in passengers' choice sets, by how many percents a 1% increase in the price of the ride would have increased the predicted probability of taking the bus. We estimate a mean cross-price elasticity of about 2, with significant heterogeneity across markets. Market-specific cross-price elasticities indeed span from less than 1 to more than 5. In particular, a relative increase in the price of a carpooling alternative induces a larger relative increase in the predicted probability of taking the bus for longer routes. These cross-elasticites also tend to be lower during peak hours than during other periods.

Finally, it is worth noting that we estimate a single model for all 15 routes simultaneously. Allowing for heterogeneous impacts of explanatory variables across routes can however be achieved either by interacting these variables with route-fixed effects, or by estimating our model for each route separately. This second approach yields average price elasticities that fluctuate between 3 and

[24] Calculations based on Uber average prices in Paris: https://www.journaldunet.fr/patrimoine/guide-des-finances-personnelles/1209180-prix-uber-2022-a-paris-et-vers-l-aeroport/

[25] Appendix D reports the corresponding estimates for market-specific intercepts.

10. Estimated route-level values of time are also somewhat heterogeneous and increase with route distance (see Appendix D). This finding is consistent with French public guidelines for cost-benefit analyses, that suggest a value of time slightly increasing in travelled distance (Quinet, 2013).

6 Counterfactual scenarios

Public policies are just beginning to realize the possible role of carpooling in a transition towards cleaner and more sustainable mobility, as well as the magnitude of the challenge to promote its large-scale adoption. The French government is for example aiming for three million "carpool" trips per day in France in 2024 (compared to less than one million today). It has therefore announced a series of measures to support carpooling, to be implemented in 2023. First, new drivers will receive a subsidy of 100 euros conditional on making a certain number of journeys during the year. Second, 50 million euros will be spent to develop infrastructure to simplify the pick-up and drop-off of passengers, such as new parking areas for carpoolers. Besides France, many other countries are implementing policies in favor of carpooling. Most prominent examples include high-occupancy vehicle lanes and reduced tolls for travellers who carpool.

We can use our estimated model to assess the impact that such public policies may have on passenger surplus, as well as on the adoption of carpooling. As an illustration, we now discuss six different scenarios. Each scenario is designed to assess the impact of a specific transportation measure that is being implemented or has been discussed in Europe or elsewhere.

First, we consider a scenario where cities increase the number of convenient meeting points for carpooling, such as designated parking spaces for carpooling or convenient drop-off lanes. The number of these parking spaces reserved for carpooling have increased significantly in many cities and rural areas in recent years. This scenario assumes that passengers are more likely to find a ride with a convenient meeting (resp. drop-off) point. Specifically, it considers that the distance between desired origin (resp. destination) and pick-up (resp. drop-off) is divided by two.

Second, we consider the creation of high-occupancy vehicle lanes on highways. This infrastructure is increasingly used to manage congestion in many countries such as the United States. In our analysis, we consider that these lanes reduce average travel time by 10%. Third, we consider the polar situation where carpool rides last 10% longer, while public transport is unaffected. This scenario is intended to represent a public policy that lowers the maximum limit speed for private cars, as is being discussed in many European countries as a way to curb carbon emissions. Fourth, we look at the impact of a 10% decrease in the price of carpooling rides. This decrease may either reflect a change in the platform's pricing structure, or a public subsidy to carpooling. Fifth, we consider a situation where the platform would disable the manual approval feature, so all bookings would be automatically approved. This situation is aimed at capturing a scenario where carpooling is so widely adopted that drivers blindly accept any prospective passenger. As a result, the overall user experience of passengers improves. Finally, we consider a counterfactual scenario termed "market maturity" where the platform has reached full penetration and all drivers have already completed at least one trip on the platform (in other words, there are no more "new" drivers). This scenario may also represent a situation in which the platform actively encourages the collection of reviews for drivers who have recently joined.

Table 9: Outcomes of our counterfactual scenarios

Scenario	Carpooling market share (vs bus) (%)	Change in number of carpoolers (%)	Mean change in passenger surplus (€/passenger)
Observed data	61.3	-	-
More carpooling spaces	68.8	+7.6	+1.70
High-occupancy vehicle lanes	65.5	+4.2	+0.82
Speed limitations	57.2	-4.0	-0.77
10% subsidy	66.7	+5.4	+1.30
100% automatic approval	62.7	+1.4	+0.28
Market maturity	61.6	+0.4	+0.07

Table 9 summarizes our results. Consistently with elasticity estimates, policies that decrease price, decrease trip duration, or improve the quality of the spatial match between passengers and drivers are found to be quite effective at promoting carpooling, inducing an increase in market share between 4 and 8%. Improving the quality of the spatial match between drivers and passengers has the highest impact, due to its larger “treatment intensity” (50% reduction in distance) relative to the other two policies (10% decrease in price or duration). Even though the corresponding increase in passenger surplus is small on a per-capita basis (1-2 €), it would scale to significant aggregate amounts, as BlaBlaCar alone claims 25 million travelers per quarter.[26]

7 Conclusion

This paper estimates the preferences of passengers for the different characteristics of long-distance carpooling trips. We rely on very detailed revealed preference data from BlaBlaCar, the largest carpooling platform in the world. In addition, we leverage our detailed knowledge of the institutional details of the platform to devise credible strategies to instrument the price and the duration of trips.

We find that passengers are very sensitive to price, with a price elasticity higher than 5 (in absolute value). In contrast, they are less sensitive to time spent in the car. We indeed estimate their value of travel time to be about 3 €/hour. This value is three to four times lower than the reference values used in cost-benefit analysis for public infrastructure, even when the reference value is tailored to leisure trips by car and expressed on a per-traveler basis (Quinet, 2013). Although carpooling is arguably more attractive to travelers with a high marginal utility of income and for trips with little timing constraints, BlaBlaCar gathers about a hundred million users and facilitates about a hundred million trips a year worldwide. Our results thus speak to a considerable volume of long-distance car trips, especially in France where about 20 million people are registered on the

[26]Source: `https://blog.blablacar.com/about-us`, last accessed in December 2022.

platform. Finally, carpoolers are found to pay strong attention to the convenience of pick-up/drop-off locations. Convenience, as measured by the distance between desired origin/destination and actual pick-up/drop-off points, is found to be one of the characteristic that passengers value the most.

A number of interesting questions are left for further research. First, a symmetric study should look at drivers' preferences and propensity to make detours to pick-up or drop-off passengers. Indeed, because passengers highly value the quality of the spatial match, efficiency improvements could be obtained if drivers' dis-utility from making a detour is lower than passengers' incremental utility from a better spatial match. Second, follow-up work should look at the extensive margin, that is, the entry of passengers and drivers on the platform subsequent to changes in its design. Such changes could include entry of different modes of transportation or changes in a number of other features of the platform.

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Appendices

A Additional background on the platform

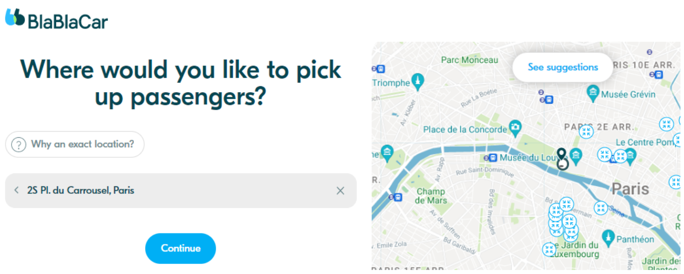
At any time, a driver with empty seats on a given trip can post a listing on the platform. She enters her departure time and location, as well as her arrival location (Figure 5a) and day and time of departure. She may also fill in locations where she is willing to make a stop to drop off or pick up passengers on her way (Figure 5b). She selects the maximum number of passengers she is willing to board (Figure 5c) and sets a price per seat for the full trip and any section thereof if applicable (Figure 5d).

On the other side of the platform, prospective passengers can search rides by entering their desired date, departure and arrival cities (Figure 6a. The platform in turn lists all the currently available rides matching these criteria (Figure 6b). It displays the full list of results in chronological order in terms of departure time. Passengers can then click on listings to get further information (Figure 6c). Finally, they may book one or several seats on their preferred trip. The booking confirmation is either instantaneous or may pend approval by the driver if she opted in manual validation.

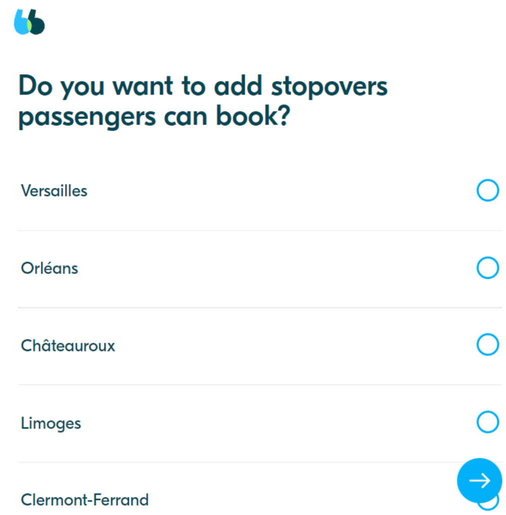
The platform charges a commission fee of around 20% of the price requested by a driver, which is included in the price seen and paid by passengers. On the main corridors between major cities, the platform also operates coach services. For these routes, search requests also return the available bus rides. A prospective passenger searching for a ride on the platform then faces a choice set composed of several carpooling rides and one or several bus rides.

Figure 5: Drivers posting process

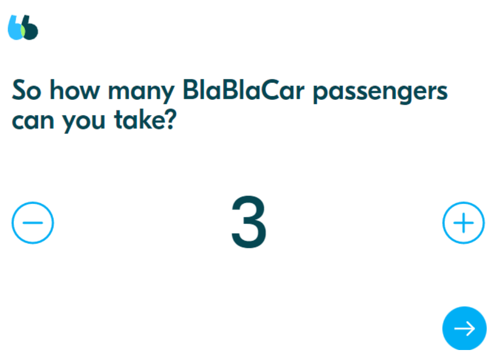
(a) Setting the pickup location



(b) Declaring stopovers



(c) Number of passengers



(d) Setting the price

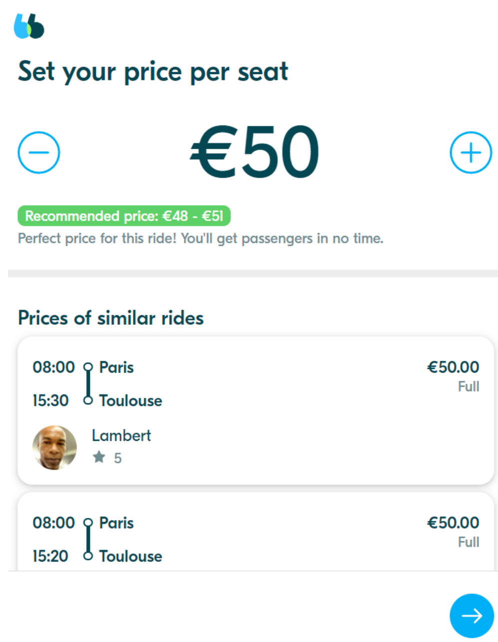
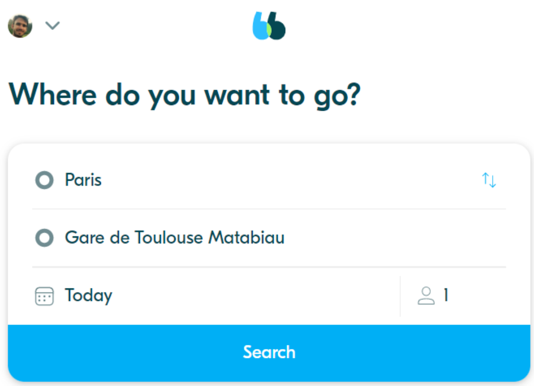
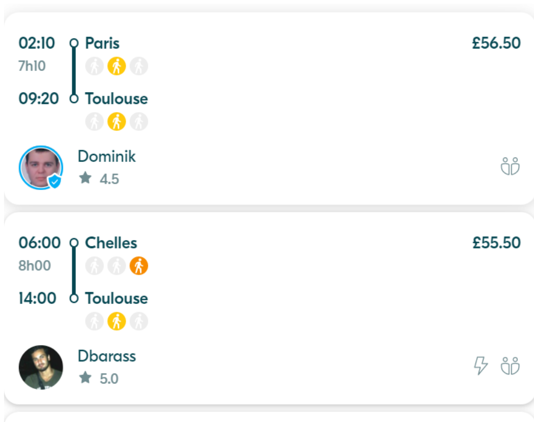


Figure 6: Passengers' search process

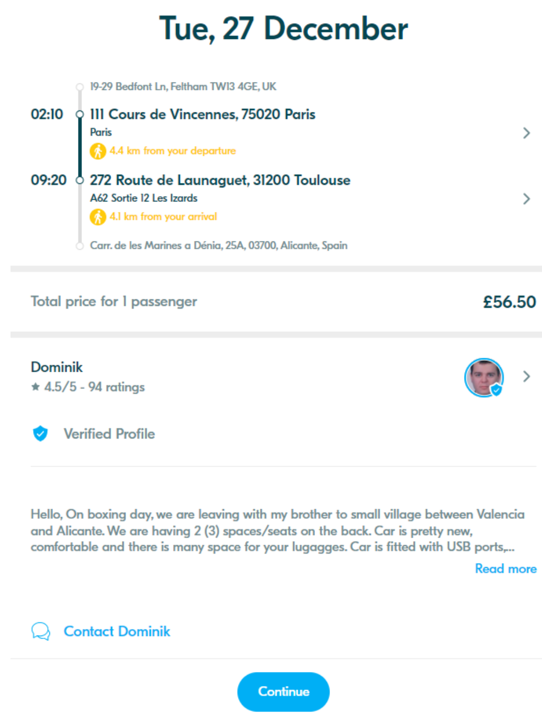
(a) Search details



(b) Search results



(c) Trip details



B Dataset construction

Raw data collection by an online platform is designed to be as exhaustive as possible. As a result, it inevitably includes a large number of noisy entries and idiosyncratic errors: bugs in data exchange protocols, bookings initiated but not completed, users refreshing pages multiple times, etc. We thus perform a number of data cleaning steps to build the dataset used to estimate our models.

Thuse models are estimated on a dataset collecting a large number of “choice situations”. In our application, a choice situation is the booking by a passenger of a given ride among the choice set that was available to her (other carpool rides and bus outside option). We select the choice situations of our final dataset as follows:

- Although a booking entry is recorded as soon as a passenger initiates a reservation, we only keep bookings for which passengers successfully paid for the ride. In other words we ignore “aborted” bookings, that is bookings for which the passenger clicked on “book the ride” but waited too long before entering her payment information so that her session expired (corresponding attrition rate: 27.5%).

- A number of bookings appear multiple times as identical data entries. Because the exact reason for the presence of such duplicates is unclear, we focus on bookings that do not appear multiple times in the raw data (corresponding attrition rate: 12.4%).

- Passengers have the ability to book multiple seats. However, the vast majority of bookings are for a single seat. Because passengers booking several seats may have on average distinct characteristics and preferences, we focus on single-seat bookings (corresponding attrition rate: 3.7%).

- When searching for a ride on the platform, a passenger can either enter a precise address for her origin/destination or instead simply enter the corresponding city. In the latter case, the platform assigns a default GPS location for each city (e.g. the GPS coordinates of the city hall) which is subsequently used when performing routing and other tasks requiring a pair of GPS coordinates. Because we find that passengers have a high valuation for the quality of their spatial match with drivers, we only keep choice situations where the passenger entered precise address for both her origin and destination (corresponding attrition rate: 52.8%).

- When building the choice set that a given passenger was facing when she booked her trip, we drop "outlier" rides, defined as rides for which the price, duration or distance is more than five times the standard deviation away from the corresponding median value for the route. If the alternative chosen by the passenger was an outlier, we drop the choice situation altogether (corresponding attrition rate: 0.04%).

- Because we use the possibility to take the bus as our outside option, we focus on choice situations where taking the bus was a possibility (corresponding attrition rate: 22.4%). When several bus rides are present in the choice set (due to different departure hours), we collapse them as a single "bus option".

- In order to have some significant variation in trips' characteristics, we only keep choice situations for which at least three carpooling rides are available (corresponding attrition rate: 5.8%).

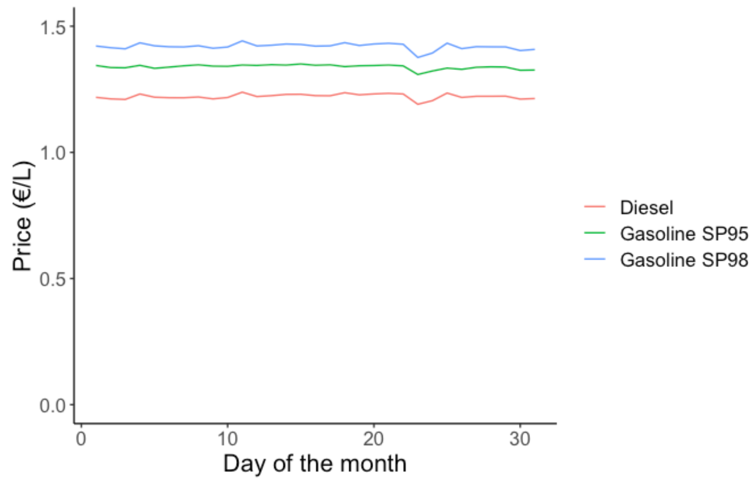
- Finally, in order to be able to identify market-specific intercepts for carpooling (relative to the bus outside option), we only keep markets – defined as a pair (axis, period of departure) – where at least ten passengers are observed to chose the bus and at least ten passengers are observed to chose a carpooling option (corresponding attrition rate: 5.1%).

We restrict attention to routes for which we are left with at least 200 choice situations, leaving us with the 15 routes studied in the paper.

C Evolution of fuel prices

This Appendix shows that there was no substantial changes in fuel prices in the study period.

Figure 7: Evolution of daily fuel prices (country average) over the study period



We retrieve daily observations of station-level fuel prices from an open data service from the French government.[27] We focus on the three main fuels sold in France: diesel, and two different types of gasoline (lead-free 95 and 98). Figure 7 shows how countrywide daily average prices have evolved over the 31 days of the study period. We observe that fuel prices were very stable over the period of our study.

D Further results

D.1 Estimates of market-specific intercepts

Table 10 reports the estimated market-specific intercepts, which are omitted for more clarity in Table 7.

[27] https://www.prix-carburants.gouv.fr/rubrique/opendata/

Table 10: Estimated market-specific intercepts

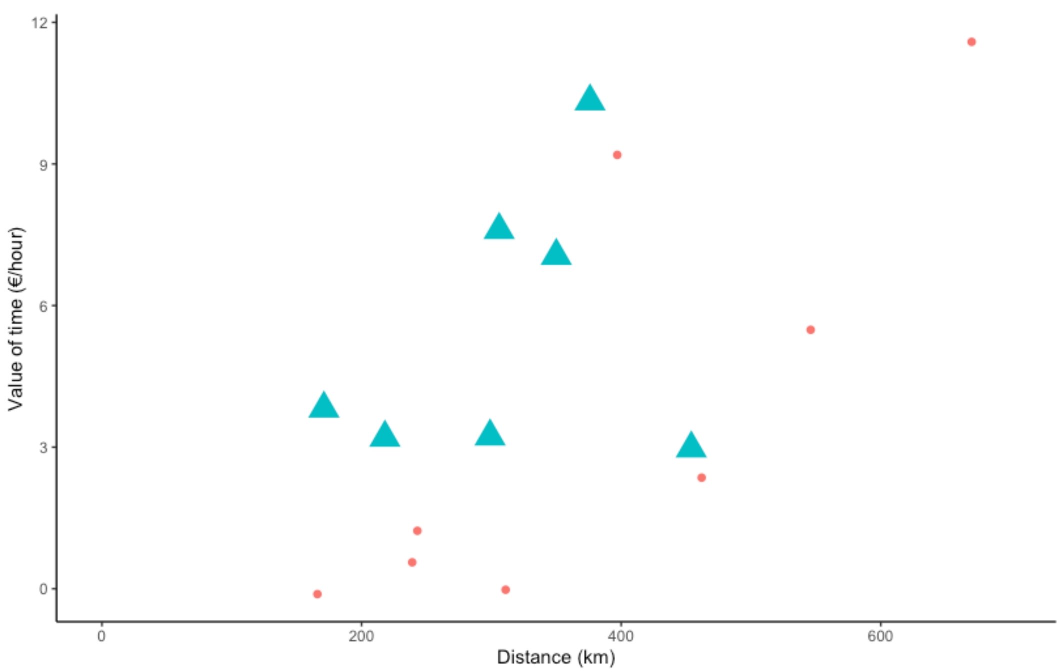
	Dependent variable:				
	choice				
	Logit	Logit	Logit	RC logit	RC logit
	(1)	(2)	(3)	(4)	(5)
is_carpool:marketr1_day	7.676 (0.522)	12.495 (0.877)	11.804 (0.946)	18.719 (1.135)	17.805 (1.211)
is_carpool:marketr10_day	0.537 (0.326)	2.388 (0.424)	2.111 (0.442)	4.099 (0.471)	3.737 (0.492)
is_carpool:marketr10_peak	0.644 (0.349)	2.452 (0.438)	2.178 (0.454)	4.509 (0.520)	4.148 (0.538)
is_carpool:marketr11_day	4.537 (0.439)	8.222 (0.695)	7.686 (0.743)	12.202 (0.846)	11.493 (0.899)
is_carpool:marketr11_peak	4.798 (0.501)	8.549 (0.743)	7.990 (0.786)	13.208 (1.066)	12.475 (1.108)
is_carpool:marketr12_day	4.363 (0.406)	7.472 (0.610)	7.010 (0.646)	11.362 (0.746)	10.753 (0.790)
is_carpool:marketr13_day	1.431 (0.348)	3.662 (0.477)	3.345 (0.506)	6.431 (0.560)	6.009 (0.596)
is_carpool:marketr13_peak	1.742 (0.388)	3.974 (0.507)	3.657 (0.534)	7.311 (0.642)	6.884 (0.671)
is_carpool:marketr14_day	4.590 (0.409)	8.147 (0.662)	7.608 (0.701)	12.353 (0.785)	11.653 (0.835)
is_carpool:marketr14_peak	5.055 (0.441)	8.716 (0.694)	8.153 (0.730)	14.347 (0.910)	13.612 (0.951)
is_carpool:marketr15_day	10.454 (0.617)	16.068 (1.026)	15.287 (1.115)	25.833 (1.479)	24.791 (1.574)
is_carpool:marketr15_night	6.439 (0.663)	12.148 (1.065)	11.347 (1.152)	13.545 (1.634)	12.516 (1.716)
is_carpool:marketr15_peak	7.598 (0.659)	13.211 (1.052)	12.434 (1.141)	18.328 (1.680)	17.297 (1.767)
is_carpool:marketr2_day	3.842 (0.385)	6.936 (0.593)	6.488 (0.634)	11.232 (0.715)	10.644 (0.763)
is_carpool:marketr2_peak	3.443 (0.404)	6.556 (0.608)	6.100 (0.646)	11.228 (0.768)	10.628 (0.812)
is_carpool:marketr3_day	0.987 (0.340)	3.190 (0.468)	2.878 (0.497)	5.498 (0.528)	5.085 (0.564)
is_carpool:marketr3_peak	1.368 (0.361)	3.555 (0.483)	3.246 (0.510)	6.464 (0.586)	6.050 (0.617)
is_carpool:marketr4_day	0.865 (0.332)	3.068 (0.463)	2.748 (0.489)	5.116 (0.515)	4.697 (0.548)
is_carpool:marketr4_night	1.280 (0.409)	3.468 (0.520)	3.149 (0.542)	5.718 (0.694)	5.302 (0.719)
is_carpool:marketr4_peak	0.962 (0.345)	3.180 (0.474)	2.856 (0.499)	5.775 (0.553)	5.347 (0.584)
is_carpool:marketr5_day	2.160 (0.386)	5.126 (0.580)	4.691 (0.617)	7.719 (0.671)	7.151 (0.714)
is_carpool:marketr5_peak	2.009 (0.450)	4.905 (0.618)	4.479 (0.650)	8.154 (0.838)	7.593 (0.867)
is_carpool:marketr6_day	2.551 (0.383)	5.394 (0.565)	4.981 (0.601)	8.856 (0.675)	8.309 (0.717)
is_carpool:marketr6_peak	2.921 (0.436)	5.761 (0.602)	5.349 (0.636)	10.057 (0.801)	9.505 (0.835)
is_carpool:marketr7_day	6.575 (0.468)	11.024 (0.802)	10.347 (0.852)	16.718 (0.983)	15.841 (1.044)
is_carpool:marketr8_day	5.073 (0.457)	9.218 (0.758)	8.616 (0.814)	13.578 (0.914)	12.790 (0.980)
is_carpool:marketr8_peak	3.668 (0.489)	7.844 (0.782)	7.235 (0.836)	11.190 (1.000)	10.405 (1.061)
is_carpool:marketr9_day	−1.071 (0.329)	0.569 (0.407)	0.340 (0.428)	1.741 (0.456)	1.438 (0.481)
is_carpool:marketr9_peak	−0.851 (0.353)	0.746 (0.423)	0.526 (0.443)	2.347 (0.503)	2.049 (0.523)
Price Instrument	no	yes	yes	yes	yes
Duration Instrument	no	no	yes	no	yes
Observations	10,114	10,114	10,114	10,114	10,114

D.2 Route-level models

Our main results estimate a single model for all 15 routes simultaneously. We can instead estimate the same model specifications for each route separately, and then look at the consistency and the heterogeneity of obtained estimates.

As an illustration, Figure 8 shows the obtained values of time when our model (specification 5) is estimated on each route separately. Overall route-level results are consistent with our main results. Mean price-elasticity fluctuates between 3 and 10, and seems to decrease as the distance of the route increases. Conversely, the estimated value of time increases with route distance, as shown on Figure 8. This finding is consistent with French public guidelines for cost-benefit analyses, that suggest a value of time slightly increasing in travelled distance (Quinet, 2013).

Figure 8: Estimated value of time as a function of the distance of the route. Red dots refer to routes for which the coefficient for duration or for price are not estimated precisely enough to be deemed as significant.



Detailed route-level results are not reported here for concision but are available from the authors upon request.

E Robustness checks

E.1 No outside option

Because passengers have several carpooling rides in their choice sets, each with different characteristics, our conditional logit models can be estimated without including any outside option. In other words, we can restrict attention to passengers who booked a carpool ride and estimate conditional logit models where passengers' choice sets consist only of carpooling alternatives.

Table 11: Obtained estimates when removing the bus outside option

	Dependent variable:				
			choice		
	Logit	Logit	Logit	RC logit	RC logit
	(1)	(2)	(3)	(4)	(5)
price_passenger	−0.189 (0.005)	−0.377 (0.023)	−0.340 (0.022)	−0.399 (0.023)	−0.360 (0.022)
duration_hours	−0.534 (0.072)	−0.573 (0.072)	−0.604 (0.111)	−0.659 (0.082)	−0.714 (0.124)
from_distance	−0.208 (0.005)	−0.215 (0.006)	−0.214 (0.006)	−0.220 (0.005)	−0.219 (0.005)
to_distance	−0.178 (0.005)	−0.184 (0.005)	−0.183 (0.005)	−0.189 (0.005)	−0.187 (0.005)
is_new_driver	−0.389 (0.061)	−0.505 (0.062)	−0.481 (0.062)	−0.520 (0.063)	−0.495 (0.063)
driver_rating_average	0.419 (0.062)	0.419 (0.062)	0.420 (0.062)	0.429 (0.064)	0.430 (0.064)
is_booking_auto_accept	0.325 (0.032)	0.169 (0.036)	0.200 (0.036)	0.165 (0.036)	0.197 (0.036)
is_two_max_back	0.035 (0.042)	−0.136 (0.046)	−0.103 (0.046)	−0.140 (0.046)	−0.107 (0.046)
starts_before	−0.376 (0.034)	−0.326 (0.035)	−0.339 (0.036)	−0.333 (0.034)	−0.348 (0.036)
continues_after	−0.405 (0.033)	−0.336 (0.034)	−0.352 (0.035)	−0.341 (0.034)	−0.359 (0.035)
match_chattiness_yes	−0.082 (0.092)	−0.105 (0.092)	−0.099 (0.092)	−0.100 (0.093)	−0.094 (0.093)
match_music_yes	0.076 (0.043)	0.070 (0.043)	0.072 (0.043)	0.073 (0.043)	0.075 (0.043)
match_pets_yes	0.168 (0.083)	0.063 (0.084)	0.083 (0.084)	0.050 (0.085)	0.071 (0.085)
match_smoking_yes	0.183 (0.106)	0.239 (0.106)	0.226 (0.106)	0.256 (0.105)	0.243 (0.105)
match_smoking_no	0.103 (0.055)	0.103 (0.055)	0.102 (0.055)	0.105 (0.055)	0.105 (0.055)
match_age_bucket	0.123 (0.033)	0.090 (0.034)	0.096 (0.034)	0.091 (0.034)	0.097 (0.034)
departnight	−2.031 (0.144)	−1.971 (0.144)	−1.980 (0.144)	−1.993 (0.142)	−2.003 (0.142)
departpeak	0.886 (0.045)	0.951 (0.045)	0.939 (0.045)	0.971 (0.044)	0.959 (0.044)
price_only_residuals		0.197 (0.023)		0.207 (0.022)	
price_both_residuals			0.158 (0.022)		0.166 (0.022)
duration_both_residuals			0.132 (0.140)		0.172 (0.148)
sd.price_passenger				0.099 (0.015)	0.098 (0.015)
sd.duration_hours				0.990 (0.222)	1.006 (0.219)
Price Instrument	no	yes	yes	yes	yes
Duration Instrument	no	no	yes	no	yes
Observations	6,178	6,178	6,178	6,178	6,178
Log Likelihood	−12,657.230	−12,618.480	−12,629.830	−12,608.820	−12,620.370

Table 11 report the obtained results, which are qualitatively similar to the ones reported in the main text.

E.2 Larger sample of passengers and heterogeneous valuations

In this exercise, the data set also includes the requests from passengers who did not specify a precise address of departure and/or arrival (i.e. they would simply type “Paris" as a place of departure, instead of a full address).

In addition, we alter our model specifications in several ways. First, rather than defining a market as a pair route$\times$period, we include two sets of carpool-specific intercepts in the utility function: route fixed effects and time of the day fixed effects. Second, we also consider a few additional controls which, though not necessary to our main message, provide interesting insight into passenger preferences. Third, we interact the price and duration coefficients with the experience of passengers with the platform, as captured by their number of existing reviews.

As shown in Table 12, our main conclusions remain qualitatively similar with larger data set and different specification. In addition, we observe that passengers highly value drivers that are similar in terms of age and preferences with respect to music, discussion, smoking and pets policy. A general preference towards younger drivers is also observed. Experienced passengers (more than 10 reviews) are generally less sensitive to the duration of of the trip. This is indicative evidence that the credibility of the trip duration – as displayed by the platform – might be affected by user experience. However, we also observe that experienced passengers have a lower marginal utility of income. This reflects some heterogeneity of preferences across experienced and non-experienced populations.

Table 12: Multinomial logit models for all routes and requests - bus outside option

	Dependent variable:				
	choice				
	Mn logit	Mn logit	Mn logit	RC logit	RC logit
	(1)	(2)	(3)	(4)	(5)
price_passenger:psgr_experienceLow	-0.193^{***} (0.004)	-0.317^{***} (0.013)	-0.317^{***} (0.013)	-0.354^{***} (0.013)	-0.354^{***} (0.013)
price_passenger:psgr_experienceMedium	-0.168^{***} (0.004)	-0.293^{***} (0.013)	-0.293^{***} (0.013)	-0.321^{***} (0.013)	-0.321^{***} (0.013)
price_passenger:psgr_experienceHigh	-0.145^{***} (0.003)	-0.270^{***} (0.012)	-0.270^{***} (0.012)	-0.293^{***} (0.013)	-0.293^{***} (0.013)
duration_hours:psgr_experienceLow	-0.688^{***} (0.100)	-0.680^{***} (0.099)	-0.750^{***} (0.113)	-0.678^{***} (0.097)	-0.938^{***} (0.132)
duration_hours:psgr_experienceMedium	-0.613^{***} (0.101)	-0.611^{***} (0.101)	-0.681^{***} (0.113)	-0.624^{***} (0.100)	-0.812^{***} (0.131)
duration_hours:psgr_experienceHigh	-0.701^{***} (0.055)	-0.700^{***} (0.054)	-0.769^{***} (0.075)	-0.725^{***} (0.054)	-0.868^{***} (0.086)
from_distance	-0.175^{***} (0.003)	-0.178^{***} (0.003)	-0.178^{***} (0.003)	-0.186^{***} (0.003)	-0.187^{***} (0.003)
to_distance	-0.160^{***} (0.003)	-0.164^{***} (0.003)	-0.164^{***} (0.003)	-0.171^{***} (0.003)	-0.172^{***} (0.003)
is_new_driver	-0.314^{***} (0.038)	-0.388^{***} (0.039)	-0.387^{***} (0.039)	-0.400^{***} (0.039)	-0.398^{***} (0.039)
driver_rating_average	0.316^{***} (0.039)	0.318^{***} (0.039)	0.317^{***} (0.039)	0.328^{***} (0.041)	0.328^{***} (0.041)
is_booking_auto_accept	0.257^{***} (0.021)	0.140^{***} (0.024)	0.140^{***} (0.024)	0.140^{***} (0.023)	0.142^{***} (0.024)
is_two_max_back	0.011 (0.027)	-0.098^{***} (0.029)	-0.100^{***} (0.029)	-0.105^{***} (0.029)	-0.106^{***} (0.029)
starts_before	-0.305^{***} (0.022)	-0.255^{***} (0.022)	-0.263^{***} (0.023)	-0.259^{***} (0.022)	-0.273^{***} (0.023)
continues_after	-0.366^{***} (0.022)	-0.306^{***} (0.022)	-0.314^{***} (0.023)	-0.308^{***} (0.022)	-0.321^{***} (0.023)
match_chattiness_yes	-0.022 (0.062)	-0.041 (0.062)	-0.041 (0.062)	-0.046 (0.063)	-0.043 (0.063)
match_chattiness_no	0.503^{*} (0.290)	0.557^{*} (0.291)	0.559^{*} (0.291)	0.589^{**} (0.280)	0.590^{**} (0.281)
driver_chatty	-0.003 (0.025)	-0.010 (0.025)	-0.010 (0.025)	-0.010 (0.025)	-0.011 (0.025)
match_smoking_yes	0.107 (0.078)	0.114 (0.078)	0.113 (0.078)	0.108 (0.078)	0.110 (0.078)
match_smoking_no	0.139^{***} (0.035)	0.135^{***} (0.035)	0.135^{***} (0.035)	0.137^{***} (0.035)	0.136^{***} (0.035)
driver_allows_smoking	-0.003 (0.036)	0.017 (0.036)	0.018 (0.036)	0.012 (0.036)	0.013 (0.036)
match_music_yes	0.284^{***} (0.032)	0.275^{***} (0.032)	0.274^{***} (0.032)	0.277^{***} (0.033)	0.278^{***} (0.033)
match_music_no	1.469 (2.262)	1.577 (2.172)	1.574 (2.177)	1.483^{*} (0.814)	1.466^{*} (0.813)
driver_likes_music	-0.108^{***} (0.027)	-0.115^{***} (0.027)	-0.116^{***} (0.027)	-0.116^{***} (0.028)	-0.116^{***} (0.028)
match_pets_yes	0.097 (0.061)	0.069 (0.061)	0.068 (0.061)	0.069 (0.061)	0.068 (0.062)
match_pets_no	-0.004 (0.043)	-0.001 (0.043)	-0.001 (0.043)	-0.001 (0.044)	-0.0003 (0.044)
driver_allows_pets	-0.018 (0.030)	-0.067^{**} (0.031)	-0.067^{**} (0.031)	-0.069^{**} (0.031)	-0.069^{**} (0.031)
driver_age_bucket25-34	-0.057^{**} (0.026)	-0.057^{**} (0.026)	-0.059^{**} (0.026)	-0.061^{**} (0.026)	-0.063^{**} (0.026)
driver_age_bucket35-44	-0.124^{***} (0.032)	-0.076^{**} (0.033)	-0.077^{**} (0.033)	-0.083^{**} (0.033)	-0.085^{**} (0.033)
driver_age_bucket45-54	-0.091^{**} (0.036)	-0.018 (0.037)	-0.018 (0.037)	-0.017 (0.037)	-0.017 (0.037)
driver_age_bucket55-64	-0.133^{***} (0.043)	-0.105^{**} (0.043)	-0.106^{**} (0.043)	-0.112^{**} (0.043)	-0.114^{***} (0.044)
driver_age_bucket65+	-0.257^{***} (0.070)	-0.263^{***} (0.070)	-0.264^{***} (0.070)	-0.269^{***} (0.071)	-0.272^{***} (0.072)
match_age_bucket	0.140^{***} (0.023)	0.141^{***} (0.023)	0.141^{***} (0.023)	0.134^{***} (0.023)	0.135^{***} (0.023)
is_carpool:is_morning	0.619^{***} (0.089)	0.545^{***} (0.089)	0.546^{***} (0.089)	0.546^{***} (0.089)	0.550^{***} (0.090)
is_carpool:is_afternoon	1.219^{***} (0.089)	1.191^{***} (0.089)	1.190^{***} (0.089)	1.210^{***} (0.089)	1.216^{***} (0.090)
is_carpool:is_evening	1.317^{***} (0.092)	1.312^{***} (0.092)	1.311^{***} (0.092)	1.327^{***} (0.092)	1.334^{***} (0.093)
is_carpool:is_peak1	-0.059^{*} (0.033)	-0.059^{*} (0.033)	-0.059^{*} (0.033)	-0.055^{*} (0.033)	0.024 (0.033)
is_carpool:is_peak2	-0.040 (0.033)	-0.041 (0.033)	-0.041 (0.033)	-0.041 (0.033)	0.016 (0.033)
sd.price_passenger:psgr_experienceHigh				0.036^{***} (0.004)	0.036^{***} (0.004)
sd.price_passenger:psgr_experienceLow				0.057^{***} (0.005)	0.056^{***} (0.005)
sd.price_passenger:psgr_experienceMedium				0.056^{***} (0.005)	0.056^{***} (0.005)
sd.psgr_experienceHigh:duration_hours				0.687^{***} (0.212)	0.707^{***} (0.202)
sd.psgr_experienceLow:duration_hours				1.056^{***} (0.221)	1.147^{***} (0.242)
sd.psgr_experienceMedium:duration_hours				0.802^{***} (0.234)	0.909^{***} (0.272)
price_residuals		0.131^{***} (0.013)	0.130^{***} (0.013)	0.138^{***} (0.012)	0.138^{***} (0.012)
duration_residuals			0.114 (0.086)		0.141 (0.092)
Price Instrument	no	yes	yes	yes	yes
Duration Instrument	no	no	yes	no	yes
Route, Time, Location FE	yes	yes	yes	yes	yes
VoT new passengers (euros/hour)	3.57	2.14	2.36	1.91	2.65
VoT junior passengers (euros/hour)	3.65	2.09	2.32	1.94	2.53
VoT experienced passengers (euros/hour)	4.82	2.59	2.85	2.47	2.97
Value Of Convenience Departure (euros/km)	1.1	0.63	0.63	0.6	0.6
Value Of Convenience Arrival (euros/km)	1.01	0.58	0.58	0.55	0.55
Own price elasticity	2.76	4.93	4.93	5.4	5.39
Observations	24,489	24,489	24,489	24,489	24,489
Log Likelihood	$-39,931.970$	$-39,875.330$	$-39,874.450$	$-39,815.560$	$-39,815.880$

Note: *p<0.1; **p<0.05; ***p<0.01