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Share the Ride: The Determinants of Long-Distance Carpooling Pricing Strategies in France*

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Abstract

This paper investigates the pricing strategies used in long-distance carpooling in France. We investigate how several factors affect carpooling prices using a comprehensive dataset of BlaBlaCar trips combined with sociodemographic and intermodal competition data. The analysis identifies two distinct pricing patterns within the platform: one characterized by standardized and consistent pricing, and another marked by more flexible, market-responsive price setting. By focusing on price per minute, we examine how trip characteristics, competitive conditions, and demand heterogeneity affect these pricing behaviors. The results show that variables such as the number of stopovers, trip length, airport or cross-border connections, and the presence of alternative transport modes influence pricing, but with contrasting effects across the two patterns. The standardized approach tends to reflect cost-sharing principles and reinforces network effects, while the more flexible approach adapts dynamically to local competition and demand.

Keywords: Carpooling, pricing strategy, platforms, intermodal competition, travel behavior.

JEL Classification: D43, L11, L91, R41, R48.

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1 Introduction

In recent years, the carpooling market has grown significantly, becoming a lucrative business opportunity and a sustainable transportation solution. Carpooling encourages private car owners to share empty seats with passengers, thereby splitting travel costs and improving vehicle utilization while reducing traffic congestion and air pollution.[1] Despite its benefits, difficulties in coordinating rides and the lack of flexibility remain significant barriers to widespread adoption (Brown, 2020).

To overcome these barriers, the proliferation of digital platforms has significantly facilitated carpooling by creating two-sided markets that connect drivers with riders (Belleflamme and Peitz, 2021). Platforms serve as intermediaries, matching supply (drivers) with demand (riders) and streamlining payment processes (Evans and Schmalensee, 2016). Achieving a balance between the needs of both user groups is a core challenge for these platforms, which include setting pricing strategies that are attractive to riders while ensuring fair compensation for drivers considering factors such as distance, duration, and fuel costs. Additionally, platforms should be responsible for ensuring user safety through measures like background checks. Despite these challenges, the popularity of carpooling platforms continues to rise as more individuals seek cost-effective and environmentally friendly transportation options.

However, platform-based mobility services do not all operate under the same model. Ride-hailing services like Uber and Lyft, classified as Transportation Network Companies (TNCs), function as professionalized transport services where the platform unilaterally sets fares. In contrast, carpooling platforms such as BlaBlaCar follow a fundamentally different approach by merely facilitating cost-sharing between private individuals who would have undertaken the trip regardless of passenger demand.[2] BlaBlaCar functions as an online marketplace that connects drivers and passengers, enabling them to split travel costs rather than generate profits (Shaheen et al., 2017). Its success is largely due to its ability to match supply and demand at scale, leveraging a trust-based digital interface that enhances user confidence and security (Saxena et al., 2020). Over time, the company has experimented with various business models—including advertising-based revenue, premium services, and B2B solutions—before establishing itself as the European leader in long-distance carpooling.[3] Today, its revenue model is based on a transactional fee structure, where passengers pay a small commission on their ride (Saxena et al., 2020).[4]

[1]See, for instance, the OECD report by the International Energy Agency (2005), as well as those by Sustainable Development Commission (2010) and Marsden et al. (2019) in the UK.

[2]'Carpooling is defined as the joint use of a motorized land vehicle by a driver and one or more passengers, carried out for no consideration, except for the sharing of expenses, in the context of a trip that the driver is making on his or her own behalf. Their connection, for this purpose, may be made for a fee.' (Article L.3132-1 of the French Transportation Code). See Section 3.1 *infra*.

[3]"In 2021, the platform had 100 million registered users, and the multinational's value was estimated at $2 billion. BlaBlaCar is the world's largest carpooling company." (Ginisti, 2024). See also Damour (2024).

[4]Several online sources provide useful overviews of BlaBlaCar's operations, its pricing mechanisms, trust-building strategies, and value creation model (Ali, 2022; Code Brew Labs, 2022, e.g.).

Building on this distinction, an intriguing aspect of the carpooling market is the interplay of factors that simultaneously influence both supply and demand. For example, routes between major cities often experience higher demand with passengers' willingness to pay premium prices. At the same time, these routes also draw more carpooling drivers, increasing competition and potentially driving prices down (Montero, 2019). This phenomenon is clearly highlighted in Farajallah et al. (2019). This dual effect underscores the complex dynamics within the carpooling market.

While previous studies have examined various facets of the sharing economy and platform-based services (Frenken, 2017), there is a relative paucity of research specifically addressing the determinants of pricing in long-distance carpooling. Understanding these determinants is crucial for policymakers aiming to promote sustainable transportation and for platforms seeking to optimize their pricing algorithms. This study contributes to the literature by providing empirical evidence on the factors influencing carpooling prices, thereby filling a research gap.

The primary objective of this paper is to identify the determinants of long-distance carpooling prices in France, specifically assessing whether carpooling services operate as a niche market or directly compete with traditional transportation modes such as trains and coaches. To achieve this, we construct an original dataset using data accessed via BlaBlaCar's API. This dataset is further enriched with information on alternative coach and train services, as well as socio-demographic characteristics of 1,260 connected cities. The analysis aimed to disentangle the various supply and demand mechanisms at play and to ascertain the influential determinants of carpooling pricing. Data was collected for two distinct dates representing periods of high and low demand: January 2, 2022, and January 24, 2022.

Within the French regulatory framework, carpooling prices are typically guided by a recommended fare, with some flexibility allowed around this reference point. Based on observed pricing patterns, this study identifies two distinct approaches to price setting in the long-distance carpooling market. One approach is characterized by clustered and stable prices, often concentrated around salient thresholds. The other shows greater dispersion, with prices varying more freely across routes and conditions. Approximately 30% of trips in the dataset follow the former pattern, while the remaining 70% correspond to the latter. This distinction provides the basis for an econometric analysis of how pricing behavior responds to route characteristics, demand conditions, and intermodal competition.

The findings reveal that several trip-level variables – such as the number of stopovers or trip duration – do not significantly affect prices when all trips are pooled together, but become influential when pricing strategies are examined separately. For example, trips with more stopovers tend to be priced lower under the more flexible pricing pattern – possibly to enhance seat occupancy – while the more stable pricing pattern is associated with higher prices on complex itineraries, likely reflecting perceived effort or service value. Similarly, routes involving large cities, cross-border travel, or airports tend to command higher fares, particularly under more structured pricing. The analysis also underscores the importance of intermodal competition: carpooling prices increase in the presence of alternative modes (e.g., coach or train), suggesting that carpooling may not systematically act as a substitute, but can also complement other transport services depending on the context.

The remainder of this paper is organized as follows: Section 2 reviews the relevant economic literature, highlighting key areas of current research. Section 3 outlines the regulatory context of carpooling in France, including platform obligations and fare structures. Section 4 describes the data utilized in the study and justifies the empirical strategy adopted. Section 5 presents and discusses the empirical findings. Finally, Section 6 concludes the paper, summarizing the main insights and suggesting directions for future research.

2 Related Literature

In this section, we provide an overview of recent studies on interurban (long-distance) carpooling, categorized into five broad themes: (2.1) determinants of modal choice, (2.2) pricing policies, (2.3) environmental impact, (2.4) behavioral factors, and (2.5) the role of carpooling in enhancing mobility in rural areas.

2.1 Determinants of carpooling choice for long-distance trips

Some of the empirical literature focuses on factors that may influence the choice to use carpooling over other alternative modes, such as train or coach. To investigate such determinants, two primary empirical approaches coexist. The first relies on real-world mobility data, such as operator-provided datasets or surveys capturing individuals' actual mobility practices and behaviors (revealed preferences). The second involves preference-based methods, including revealed preference studies or stated preference surveys. Among the latter, discrete choice experiments (DCE) are particularly prominent, as they enable researchers to simulate hypothetical modal choice scenarios, allowing for a deeper understanding of decision-making processes.

Using a DCE approach, de Luca and Pace (2015) analyzed long-distance commuting trips and modal choice and found that carpooling services may be a substitute for the coach mode. The low-cost positioning of carpooling is a determining factor in the transport modal choice. Sharing the costs makes carpooling economically competitive compared to solo driving or other travel modes (Shaheen et al., 2017; Brown, 2020). Indeed, evidence from DCE studies indicates that low-income individuals are more likely to participate as passengers, whereas high-income individuals often take on the role of drivers (Monchambert, 2020). Le Boennec et al. (2024) confirm that economic incentives remain a strong lever for carpooling adoption across different personality profiles. Students, for example, are a type of customer in favor of carpooling (Shaheen et al., 2017). In terms of individual characteristics, travel expenses, access time to parking lots, gender, age, frequency, and car availability are the most significant factors that influence the choice probability of carpooling. On average, drivers tend to make long-distance trips and detours to pick up or drop off passengers (Dong et al., 2018).

Based on revealed preference data from BlaBlaCar, Astier et al. (2023) analyzed long-distance carpooling trips in France from the passengers' perspective by estimating passengers' preferences. Astier et al. (2023) found that the price elasticities of carpooling services are quite high, and passengers value the convenience of pick-up and drop-off locations. In contrast, once in the car, the value of time is quite low, ranging from €3/h to €10/h when data are disaggregated at the route level.

2.2 Carpooling and pricing strategy

The pricing policy of sharing platforms, such as carpooling, is a two-sided business model (Zhu, 2020; Malardé and Pénard, 2022; Yeung and Zhu, 2022). BlaBlaCar is a successful carpooling platform (Saxena et al., 2020), and previous empirical literature has provided insight into the pricing scheme of carpooling platforms based on firm data. For instance, Farajallah et al. (2019) show that user recommendations play a decisive role in setting fares. Based on BlaBlaCar data, the average price for a trip is €13, with high dispersion (€9.4). The average price is €2.8 lower than the recommended price, indicating that the recommended price is not serving as a market price benchmark. In terms of individual characteristics, experienced (high rating) drivers set lower prices than less-experienced drivers, with a moderate effect size. Moreover, experienced drivers have higher seat occupancy. Farajallah et al. (2019) identify four individual effects. First, a *gender effect*, whereby female drivers set prices that are 12 cents higher than male drivers, on average. Second, an *age effect*, whereby older drivers set higher prices and, controlling for price, sell fewer seats on average. Third, a *learning effect*, where drivers who initially experienced no socialization benefits from the platform learn to price in ways that attract riders. Fourth, a *demographic effect*, where having an Arabic name significantly reduces the driver's demand and revenue.

Yeung and Zhu (2022) examined BlaBlaCar data during the 2018 French railway strike as a case study and found that the number of offered seats increased by 6% and the number of booked seats rose by 33% on average strike days. Despite the spikes in demand, prices remained stable during the strike, which was attributed to BlaBlaCar's price recommendation mechanism that upholds the cost-sharing principle on ridesharing platforms. The study highlights the importance of price stability and voluntary compliance in maintaining transportation system resilience during abnormal market conditions.

2.3 Carpooling and the environment

While carpooling was initially identified as a potential solution to reducing the carbon footprint of travel (Delhomme and Gheorghiu, 2016; Yin et al., 2018), economic literature has provided a more nuanced perspective on this claim. In 2018, carpooling helped avoid

272,746 tons of CO2 emissions in France, with an average distance of about 239 km per trip and an average of 3.5 people per vehicle (BlaBlaCar, 2019). To contextualize this figure, total CO2 emissions from passenger cars in France amounted to approximately 67.12 million metric tons in 2022. This means that the emissions avoided through carpooling in 2018 represent around 0.41% of total annual emissions from passenger vehicles.[5] While modest in relative terms, this reduction highlights the role that carpooling can play as part of a broader strategy for decarbonizing personal mobility.

Various studies have analyzed the environmental impact of increased carpooling and how public measures can foster sharing schemes. Yin et al. (2018) investigated the CO2 emission mitigation potential of carpooling in the Paris area, using an integrated land-use transport model that combined two existing transport and land-use models. Their findings suggest that carpooling holds significant potential for reducing CO2 emissions. Assuming a 50% increase in the average number of carpool passengers, CO2 emissions could be reduced from 11% to 18%, depending on the period.

However, while carpooling reduces travel costs for passengers, it also lowers expenses for drivers, potentially incentivizing them to travel more frequently. Given that carpoolers tend to be more mobile compared to the general population, this could lead to an increase in the number of vehicles on the road, ironically counteracting the original goal of reducing traffic (rebound effects). As highlighted in the study by ADEME (2015) for long-distance carpooling,[6] this phenomenon suggests that the potential benefits of carpooling in reducing the overall CO2 emissions may be offset by the increased mobility of carpool drivers. Olave-Cruz et al. (2025) identify the conditions under which carpooling can mitigate the carbon footprint. To this end, the authors establish a robust metric based on the alternative modes of transport that travelers (both drivers and passengers) would have used in the absence of carpooling, thereby accounting for both the volume effect and the modal shift effect. They define a threshold occupancy rate beyond which carpooling effectively reduces the carbon footprint of travel. For instance, using a representative sample of routes in France, the authors demonstrate that filling empty seats could generate carbon savings ranging from 0.52 to 0.63 tCO2 per route and per day.

Carpooling offers significant benefits in terms of fuel consumption. In the U.S., Jacobson and King (2009) demonstrated that if no additional travel is required to pick up passengers, adding one passenger to every ten vehicles would result in fuel savings of approximately 7.54 to 7.74 billion gallons of gasoline per year. Regarding gasoline savings in France, in 2019, gasoline-powered passenger cars in France consumed an average of 7.1 liters per 100 kilometers. Given that carpooling trips averaged 239 km, this translates to approximately 17 liters of gasoline per trip. With an average of 3.5 people per vehicle, carpooling effectively reduces the number of separate trips, leading to substantial fuel

[5]Source: `https://www.statista.com/statistics/1497321/cars-carbon-dioxide-emissions-in-france`.

[6]According to this study, 21% of drivers surveyed stated that they would have traveled less if not for carpooling.

savings over time.[7]

At the individual level, environmental reasons do not play a decisive role when choosing carpooling (Amirkiaee and Evangelopoulos, 2018). Therefore, government and local authorities should further encourage the use of carpooling and its ecological impact. In this context, Si et al. (2022) found that information publicity not only positively influences carpooling intention but also increases carpooling behavior. Interestingly, government regulations have a stronger impact on female users, users with higher education levels, and younger users. Carbon emission reduction certification[8] may have a negative effect on female users' carpooling behavior. Information advertisement is also effective in improving older people's usage of carpooling.

2.4 Psychological and behavioral factors

Psychological and emotional factors play a role in the decision-making process between driving alone and carpooling (Amirkiaee and Evangelopoulos, 2018; Bachmann et al., 2018). Amirkiaee and Evangelopoulos (2018) found a positive relationship between economic benefit, time benefit, transportation anxiety, and trust regarding carpooling, as well as a positive relationship between reciprocity and trust with the intention to participate in carpooling. Interestingly, commitment to community, sustainability concern, altruism, and enjoyment of being social were unrelated to their attitude towards carpooling participation. Their study focused on individual-level decision making and found that people would choose carpooling in situations where transportation anxiety is high if they could trust the carpooling service providers and participants, given the presence of economic and time benefits.

In the realm of behavioral studies, the significance of trust in platforms and the risk propensity of participants have been underscored (see Wang et al. (2016) or Marth et al. (2022) in a platform context unrelated to carpooling). Adding to this, Tsai et al. (2021) examined the intention to use carpooling services in Bangkok, Thailand, using a framework that combines social exchange theory and self-determination theory. Their analysis of 409 respondents revealed that while trust could mitigate privacy risks, it had no significant impact on consumers' overall intention to use carpooling. Moreover, perceived risk was also found to have no direct effect on usage intention. Instead, perceived value—shaped by sustainability, enjoyment, and economic benefits—emerged as a key driver. These findings enrich the literature by suggesting that in emerging markets like Thailand, the motivational factors influencing carpooling may differ, with enjoyment being a stronger motivator than sustainability or economic concerns.

[7]Source: `https://www.statista.com/statistics/1105126/consumption-of-fuel-average-passenger-car-france`.

[8]Dida, a carpooling service provider in China, proposed a carbon-emission reduction certification (CERC) program. The company computes and warrants the carbon emissions reduced by each user's carpooling behavior.

2.5 Carpooling and rural areas

Recent studies have highlighted an increasing interest in promoting carpooling services in rural or low-density areas. According to Nakanishi et al. (2021), carpooling trips can be categorized into three classes based on origin-destination pairs: low-density areas, inter-metropolitan, and others. In regions with low population density, residents often heavily rely on private vehicles.

Rotaris and Danielis (2018) examined the role of carpooling in such contexts and suggested that carpooling platforms should adopt a socially oriented business model. In the Friuli Venezia Giulia region of Italy, 3.7% of the population indicated a willingness to use carpooling services. Potential users are mainly students, unemployed individuals, environmentally conscious people, and those who are better informed.

From a public policy perspective, Chamorro-Obra and Fukuda (2020) investigated the implementation of economic incentives for intercity carpooling platforms to encourage drivers to stop in small towns along their routes. Simulation results demonstrated that social welfare is maximized when the economic incentive is approximately 3.3 times the value of travel time under equilibrium conditions of supply and demand. However, individual welfare gains were minimal, and the incentive negatively impacted social welfare when passengers highly valued travel time. Moreover, the incentive consistently had an adverse effect on the platform provider's income.

Mohammadi-Mavi et al. (2024) explored factors influencing the willingness to carpool in rural-to-urban commutes in areas lacking public transit options, such as Perry County in Pennsylvania. Utilizing a structural equation model based on survey data, the study identified *time flexibility*—the willingness to tolerate additional commute time—as a crucial factor affecting carpool adoption. Environmental awareness and cost sensitivity positively correlated with an inclination to carpool, while preferences for privacy and autonomy acted as deterrents. Monetary incentives increased willingness among lower-income and cost-sensitive individuals but were less effective for high-income, time-sensitive commuters. The authors concluded that non-monetary incentives, such as dedicated lanes or parking privileges, might better appeal to higher-income groups.

Lastly, Talandier et al. (2024) examined the territorial impacts of carpooling through BlaBlaCar in France, uncovering several key dynamics. The urban hierarchy significantly influences carpooling demand, with major cities exhibiting the highest usage. Paris emerges as the primary hub, though intermediate cities like Lyon and Marseilles also play essential roles. While smaller towns contribute less to overall carpooling flows, they are vital for ensuring regional connectivity. Carpooling links vary based on distance; regional connections between large and intermediate cities, especially in tourist areas, show high demand and often serve as alternatives to less frequent train or bus services. In rural and peripheral regions with limited public transportation options, BlaBlaCar provides a crucial mobility solution, connecting these areas to nearby urban centers and popular tourist destinations like the Alps and the Pyrénées.

3 Carpooling as a two-sided market

Carpooling is not a new concept and has been in practice for a long time, particularly with an increased preference for the use of cars in urban and suburban areas during the 1970s. Furthermore, the advent of digital platforms for connecting drivers and passengers has greatly boosted the use of carpooling, especially for long-distance trips, over the past fifteen years. In France, carpooling's modal share was around 1.6% in the mid-2010s, with an estimated developmental potential of 3.5%-4% in less than 10 years (ADEME, 2015). To achieve this growth, a better understanding of the regulatory and legal aspects of carpooling (3.1), the roles and obligations of the platforms connecting drivers and passengers (3.2), as well as their pricing strategies (3.3), is essential.

3.1 Definition of carpooling

In France, carpooling is officially defined in Article L.3132-1 of the Transportation Code, as amended by Law No. 2019-1428 of December 24, 2019, on the orientation of mobilities,[9] "*Carpooling is defined as the joint use of a motorized land vehicle by a driver and one or more passengers, carried out for no consideration, except for the sharing of expenses, in the context of a trip that the driver is making on his or her own behalf. Their connection, for this purpose, may be made for a fee.*" Thus, two conditions must be met for a proposed trip to be considered carpooling: First, it must be part of a trip made by the driver for his or her own account, and second, it must involve cost sharing between the driver and passengers. This legal definition implies that carpooling is a non-professional activity, which differentiates it from passenger transport services.

Decree No. 2020-678 of June 5, 2020, specifies the nature of carpooling expenses considered (Art. R.3132-1), as well as the notion of shared expenses (Art. R.3132-2). Regarding the first point, the expenses considered are those incurred by a driver for using his or her vehicle (vehicle depreciation, maintenance and repairs, tire and fuel consumption expenses, insurance), to which toll and parking expenses may be added if necessary.[10] Concerning the second point, the sharing of expenses is done at the discretion of the driver and passengers in such a way that they freely determine.[11] As long as these conditions are met, the financial transactions for both groups are not subject to VAT.

3.2 Obligations of driver-passenger connecting platforms

Digital platforms, including carpooling sites, enable the connection between drivers and passengers for a fee, usually in the form of commissions on financial transactions. These platforms are required to provide fair, clear, and transparent information about their terms of use and online offers' referencing and ranking methods.

[9] This law is commonly known as "Loi d'orientation des mobilités," and the acronym used is LOM.

[10] The tax scale of mileage expenses can serve as a reference.

[11] On its website, the Ministry of Ecology recommends setting carpooling offers at or below 0.20 €/km per passenger, in reference to the maximum tax scale of 0.60 €/km.

In its practical guideline on carpooling regulations, the Direction générale de la concurrence, de la consommation et de la répression des fraudes (DGCCRF) (2023) recommends that compliant sites "*advise drivers on the maximum amounts they can ask from passengers for sharing expenses and warn them in case of excess fees that could lead to the requalification of the financial exchange as a professional activity of illegal transport.*" The DGCCRF stipulates that these warnings or alerts must be based on the distance and the number of passengers, as expenses are intended to be shared.

3.3 Pricing methods of driver-passenger connecting platforms

There are several driver-passenger connecting platforms offering carpooling services, with options such as short, medium, or long-distance, and scheduled or not. These platforms may be associated with entrepreneurial, cooperative, associative, or pro-environmental organizations, and their services may be free or paid. For instance, Klaxit and Karos focus on short-distance, daily commuting, often supported by local governments and employers through incentive programs. Mobicoop and Covoiturage-libre operate as cooperative or community-driven initiatives, emphasizing accessibility and sustainability over profit. Internationally, platforms such as Poparide in Canada and Zimride in the United States provide regional carpooling services, particularly for university students and commuters. Some services, like inDrive, blend elements of carpooling with ride-hailing by allowing price negotiation between drivers and passengers. These diverse models highlight the variety of approaches in the carpooling ecosystem, where pricing mechanisms and operational structures can vary significantly.

As for BlaBlaCar, the platform provides a suggested price for each journey, calculated based on distance, estimated fuel costs, and tolls. However, drivers retain the flexibility to adjust this price within a predefined range, allowing them to account for specific route conditions, demand fluctuations, or personal preferences. Unlike TNCs such as Uber or Lyft, where the platform centrally determines fares, BlaBlaCar operates as a facilitation service, allowing drivers to set their own prices within a suggested range. This structure introduces an element of market dynamics where pricing may vary based on driver preferences and demand elasticity. For example, for long-distance non-scheduled trips, the BlaBlaCar platform's recommended price is based on the calculation rule of €0.048 per kilometer and per seat for a trip without any toll road section and €0.065 per kilometer and per seat for a toll road section trip (Farajallah et al., 2019). The driver can adjust this recommended price within the limit of ±50%.

BlaBlaCar is testing an optimized pricing system that suggests prices based on the day and time of departure to increase the probability of selling all available seats. Drivers can still adjust these optimized prices by up to 50%. This shift from a recommended price to an optimized price aligns with the findings of Farajallah et al. (2019). This study differentiated between the recommended price (referred to as BlaBlaCar) and the price set by the driver (referred to as Driver) within ±50% of the recommended or optimized price.

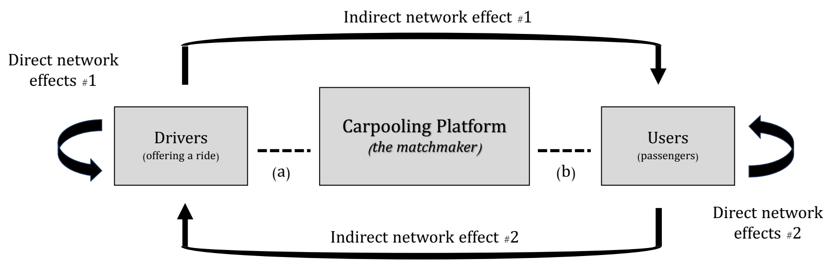

Figure 1: Carpooling as a two-sided market

Figure 1 illustrates the two-sided nature of the carpooling market, characterized by its reliance on network effects. BlaBlaCar serves as a platform that facilitates the connection between drivers and passengers seeking to meet their travel needs. Notably, indirect network effects play a pivotal role within the carpooling ecosystem. As the number of drivers offering available seats on the platform increases, passengers' utility rises significantly as their chances of finding a suitable trip are enhanced. Conversely, a surge in active passengers on the platform motivates more drivers to list new trips, bolstered by their increased confidence in securing bookings for one or even multiple seats in their vehicles. These dynamics are visually depicted by the arrows at the top and bottom of Figure 1.

Additionally, it is important to recognize the presence of direct network effects, which may not be as readily apparent but are nonetheless discernible. A growing community of BlaBlaCar drivers contributes[12] to an increased sense of belonging among users who are committed to shared environmental and mobility concerns, ultimately amplifying their overall utility. A similar effect can be observed among passengers who utilize a carpooling platform. These direct network effects are visually represented by the arrows on each side of the market, as illustrated in Figure 1.

3.4 Testable hypotheses

Informed by a comprehensive review of the existing literature and the unique intricacies inherent to carpooling as a two-sided market, this section posits a set of testable hypotheses (refer to Section 4 for original data sources).

3.4.1 Regulatory constraints and cost-sharing

The legal framework surrounding carpooling, along with its inherently non-professional status, allows for the equitable distribution of travel expenses among participants (see section 3.1). For a driver offering multiple seats, it can be assumed that they would be inclined to reduce the price for any additional seat sold in order to maintain a cost-sharing

[12]See the report on the social impacts of carpooling by BlaBlaCar (2018).

logic and avoid having their activity classified as professional, in which case they would be required to pay value-added tax (VAT). Under such constraints, it is hypothesized that:

Hypothesis 1 *The per-seat pricing in carpooling exhibits a downward trend as the number of seats sold increases.*

3.4.2 Airport-related routes

Airport-connected routes possess distinct characteristics shaped by both economic and logistical variables. First and foremost, airports are hubs of high demand for travel, with both local and international travelers looking for convenient modes of transportation. This high demand often intersects with limited or less convenient public transportation options, making carpooling a preferred choice. Additionally, the time-sensitive nature of airport travel makes reliability a premium that many are willing to pay for.

Geographic and temporal factors also come into play. Airports are frequently located far from city centers or residential areas, requiring longer trips that are costly. Routes to airports often involve navigating busy roads and highways prone to traffic congestion, adding another layer of complexity and risk that could justify higher prices. Moreover, flights operate round the clock, leading to carpooling demands at odd hours, which may involve additional charges.

Operational costs like tolls or fees on certain routes and potential waiting times for pick-up at airports can also contribute to higher prices. Specialized carpooling services may emerge to cater to the unique needs of airport travel, such as extra luggage space and higher reliability. These specialized services might be priced higher than standard carpooling options. To conclude, high demand, constrained public transport options, and the premium placed on reliability jointly contribute to:

Hypothesis 2 *Carpooling prices are generally higher for airport-connected routes.*

3.4.3 Cross-border routes

International border crossings introduce both regulatory and logistical complexities, thereby affecting pricing. Regulatory requirements such as different transportation laws and the potential need for special permits or certifications can increase drivers' costs. Similarly, the dynamics of supply and demand tend to inflate prices, particularly if the demand for cross-border routes outpaces the supply, which is often limited due to the added complexities of international travel.

Factors related to geography and infrastructure also contribute to higher costs. For example, longer distances and possible detours for checkpoints inherently result in greater expenses. Additionally, psychological factors, such as the perceived reliability and the avoidance of strikes often associated with carpooling services can encourage the payment of a premium.

Finally, the time spent on border formalities is a notable operational cost that can be passed onto the consumer. Given these multiple factors, it is reasonable to assume that carpooling prices would be higher on routes that cross international borders. In Blayac and Bougette (2017), this effect was observed, notably on rail and, to a greater extent, in the case of carpooling. Thus, the following hypothesis can be formulated:

Hypothesis 3 *Cross-border carpooling routes are associated with higher prices.*

3.4.4 Market competition on high-transaction routes

Routes characterized by a high volume of transactions likely signal that supply either meets or surpasses demand, thereby fueling competition among service providers. In such a market, drivers will compete against each other to attract riders. This intramodal competition generally leads to lower prices in order to entice customers.

Network effects can also play a role here. As more people use the service, the value of the service for each user increases, encouraging even more users, and this may encourage lower prices while maintaining profitability. Thus, the following hypothesis is stated:

Hypothesis 4 *Routes with strong intramodal competition tend to feature lower average carpooling prices.*

3.4.5 Influence of stopovers

The number of stopovers along a route impacts the pricing dynamics in favor of passengers. Two effects work in tandem. First, allowing more stopovers on a route effectively increases the supply of seats since a single car can pick up multiple passengers throughout the journey. Second, each individual stopover generally experiences lower demand. While the aggregate demand for the entire route may remain constant, the specific demand at each stopover is likely to be less than the demand for the full route. The combination of these two factors typically results in lower prices for individual passengers, especially for those who are flexible with pickup and drop-off locations.

Additionally, cost-sharing mechanisms come into play. The more stopovers and, consequently, the more passengers a carpool can accommodate, the more opportunities there are to distribute both fixed and variable costs. As a result, the individual cost for each passenger tends to decrease. Thus, the following hypothesis can be formulated:

Hypothesis 5 *Increased stopover points are associated with a decrease in individual fares.*

3.4.6 Advance booking

With regards to price dynamics, booking in advance allows carpool providers to better plan their trips and optimize routes, which potentially reduces their costs and might incentivize them to offer lower prices. Advanced bookings also provide the driver with the assurance that specific seats are sold, reducing the risk associated with vacant seats and potentially leading to lower prices.

From the perspective of price discrimination, consumers booking at the last minute are often less price-sensitive and may be willing to pay a premium. On the other hand, those booking in advance are more likely to be price-sensitive and may shop around, which can pressure providers to offer lower initial prices. When it comes to operational costs, trips booked in advance allow for more efficient administrative tasks such as route planning and passenger coordination, and these savings could benefit consumers.

Competition also plays a role. Offering lower prices for trips booked in advance can be a competitive strategy used to secure passengers before they choose other options. Thus, the following hypothesis can be formulated:

Hypothesis 6 *Early booking is associated with a lower average fare.*

3.4.7 Intermodal competition

The availability of alternative modes of transportation necessitates competitive pricing strategies (Fageda and Sansano, 2018, e.g.). When multiple transportation options are available, consumers are more likely to gravitate toward the most cost-effective, convenient, or fastest method. This puts pressure on carpooling services to price their offerings competitively.

In a market where railways and coaches[13] are also vying for consumer attention, price wars can ensue (Blayac et al., 2024). These established forms of transportation may lower their prices in response to competition, prompting carpooling services to do the same. Unlike traditional transportation systems, which often have high fixed costs, carpooling usually has a more flexible cost structure. This flexibility makes it easier to adjust prices dynamically based on real-time demand and supply.

This dynamic pricing model through online platforms allows carpooling services to lower their prices accordingly when competition is high. Lower prices can also be a market penetration strategy, especially in markets dominated by other forms of transport. While price is a significant factor, carpooling services can also compete by improving user experience, although such improvements usually follow the establishment of a robust user base, which is easier to secure when prices are low, resulting in the following hypothesis:

Hypothesis 7 *Strong intermodal competition exerts downward pressure on carpooling prices.*

These seven hypotheses are tested on the detailed and exhaustive sample obtained from the European carpooling leader. The next section presents the original data used in

[13]See Blayac and Bougette (2017) for an analysis of the long-distance coach market in France and Duberga (2021) in the UK. Both carpooling and coach services target a similar customer base and may share a platform business model. A case in point is the takeover of the French coach company Ouibus by BlaBlaCar in 2019, which gave rise to the BlaBlaBus brand. See Blayac and Bougette (2023) on the consolidation of the French long-distance coach market.

this study.

4 Methodology

This section details the methodological approach used for data collection and data cleaning.

4.1 Data collection

Empirical search results from BlaBlaCar[14] and Comparabus[15] were collected at multiple points in time across many city pairs in France. The 30 most populated cities in metropolitan France were used as reported on the website of L'Internaute,[16] excluding cities that are not departure or arrival points on BlaBlaCar or Comparabus. The six airports with the largest possible daily flows of passengers at departure/arrival points were also included (Autorité de régulation des transports (ART) (2020) and DGAC, 2019).[17] This approach led to 1,260 possible origins/destinations, where each of the 36 departure points had 35 possible destinations. These 1,260 origins/destinations constitute routes of interest and include routes with both high and low volumes of passengers, as well as specific passenger types, including city centers to airports as origin/destination.

BlaBlaCar kindly provided us with an API key, allowing for the collection of data on search results and trip details across 1,260 routes of interest. The API key provides access to information such as prices, the number of seats available, trip distance, duration, departure/arrival time, the number of stopovers, BlaBlaCar commission, specific pick-up/drop-off addresses, and additional trip characteristics. Due to privacy concerns, BlaBlaCar did not provide access to individual driver's data, such as their name, ratings, gender, age, number of previous trips, and so on.

To understand the different demand dynamics in terms of both high and low demand, we collected data for BlaBlaCar journeys on two departure dates: January 2, 2022, the Sunday following New Year's celebrations, when passenger volumes were expected to be high (hereafter referred to as 'high-demand' trips), and January 24, 2022, a Monday outside any national holiday periods, when passenger volumes were expected to be low (hereafter referred to as 'low-demand' trips).

To analyze the variation in the number of trips supplied, the number of seats available, and the prices as the departure date approached, information was extracted at several points: a week before departure (D-7), three days before (D-3), and a day before (D-1). This approach was used for the trips at times of both high and low demand. This approach provided information on when a seat was booked, as can be seen with regards

[14]See https://www.blablacar.fr

[15]See https://www.comparabus.com/en

[16]See https://www.linternaute.com/ville/classement/villes/population

[17]This includes Lyon Saint Exupéry Airport (LYS), Paris Charles de Gaulle Airport (CDG), Paris Orly Airport (ORY), Nice Côte d'Azur Airport (NCE), Marseille Airport (MRS), Basel Mulhouse Freiburg EuroAirport (LFSB).

to the number of seats left that vary across the D-7, D-3, and D-1 information. More will be discussed specifically the assumptions involved later on.

Furthermore, data was collected on alternative transportation modes by web-scraping Comparabus, a price comparison website that provides information on coach, train, and flight trips. Scraping codes were used for departures on both January 2nd and 24th 2022, at D-7, D-3, and D-1 before departure. The extracted data includes details on the coach/train/flight operator, price, duration, departure/arrival times, and number of stopovers. However, it was noted that the flight trip data reported excessively large durations or prices, and caution was exercised when analyzing this information. Therefore, this article will not present any results or summary statistics specific to flight trips.

Comparabus also reports search results for carpooling trips. As this information aligns with the search results directly extracted from BlaBlaCar; however, this information was excluded as it is less detailed.

Overall, this data collection strategy resulted in a massive number of observations from the BlaBlaCar and Comparabus raw search results (see Table 1).

Table 1: Number of observations extracted - Raw search results

High demand	***Departure on January, 2^{nd}, 2022***		
Days before	Carpooling	Coach	Train
D-7	16,534	6,105	3,141
D-3	25,752	6,142	3,282
D-1	28,438	6,167	3,250
Low demand	***Departure on January, 24^{th}, 2022***		
Days before	Carpooling	Coach	Train
D-7	3,359	3,099	7,128
D-3	8,239	3,088	6,351
D-1	11,944	3,023	6,647

Regarding carpooling, the reported data highlights the significant variation in the total number of trips supplied as the departure date approached. In contrast, the number of trips supplied by coaches and trains remained more stable as the departure date approached. Coach operators are very responsive to high demand departures, with twice as many trips supplied on January 2nd than on January 24th. However, the supply of train journeys does not respond to high demand. On the contrary, the number of trips available is halved during weekends of high demand. This is likely due to the limited staff availability during holiday periods.[18] The data collection process described above has allowed us to gather an extensive dataset on carpooling, coach, and train trips. The BlaBlaCar API key has enabled the collection of very granular carpooling trip information, and the scraping of Comparabus led to the main alternate options available for passengers traveling on January 2nd and 24th, 2022. As mentioned above, extensive demographic information

[18] It is also likely due to the beginning of a new epidemic wave of Covid-19 (Omicron variant) which forced the SNCF to reduce its rail offer in January 2022, see Daboval (2022).

for the departure/arrival cities in the dataset has been scraped from the *L'Internaute* website. This allowed for the control of key variables such as population, average income, proportion of young/senior people, proportion of students, and additional information that can drive demand for carpooling services in the origin/destination cities.

Overall, extensive information has been gathered on the characteristics of carpooling trips, alternative transportation modes available, and socio-demographic information in the cities of departure and arrival. This allowed for exploring the main determinants of carpooling prices and passengers' flows in times of both high and low demand.

4.2 Data cleaning

In this section, the steps taken to clean and preprocess the datasets used in the analyses are outlined. The goal of the data cleaning process was to ensure consistency, remove duplicates, and format the data in a way that would allow for accurate and meaningful comparisons. Tailored cleaning methods were used for each dataset, considering their specific characteristics and challenges. The following subsections describe the detailed procedures applied to the BlaBlaCar and Comparabus datasets.

4.2.1 The BlaBlaCar dataset

Prior to analysis, several data cleaning steps were implemented for the raw data obtained from BlaBlaCar. Initially, all search results were collected, where the pick-up or drop-off point was within 50 kilometers of the city centers. This approach was done to ensure a comprehensive data collection process. However, this resulted in duplicate search results for cities located very close to each other. For instance, a departure towards Paris with a pick-up point between Marseille and Toulon would appear under both Marseille-Paris and Toulon–Paris in our data. To address this issue, the data was restricted to all search results where the pick-up and drop-off points were within 20 km from the city centers. The distances were calculated as the geographic distance between the coordinates of the pick-up/drop-off points and the coordinates associated with each city on the BlaBlaCar website, specifically the city centers.

Secondly, BlaBlaCar data was reshaped into a wide format used to create a dataset with only one row per unique trip. This allowed for merging the D-7, D-3, and D-1 datasets and analyzing how trip details such as prices, available seats, and number of stopovers varied over time.

However, using this dataset for analysis posed a problem. At this stage, the data included all supplied trips, including those that were not eventually booked by passengers. Including these departures could overestimate the carpooling prices as these trips were likely to be more expensive or have trip details that were less advantageous for passengers, which could explain why no one booked them.

Therefore, the third data cleaning step transformed the current dataset with one observation for each listed trip to a dataset at the transaction level. The number of seats available was used to determine the number of seats purchased over time. For example, if a trip reported three seats available at D-7 and only two at D-3, it was inferred that one seat was booked between D-7 and D-3. If only one seat was available at D-3, it was inferred that two seats were booked, and the transactions level dataset would have two rows for that trip. If a trip disappeared from the dataset between D-7 and D-3, it was assumed that the number of seats available at D-7 was fully booked during the next four days. The same logic was applied when comparing seats available between D-3 and D-1.

The approach used in this study is predicated on two assumptions. Firstly, it presupposes that BlaBlaCar drivers do not decrease the number of available seats over time, so any reduction in the number of available seats would be due to booking. Secondly, it assumes that they do not cancel their trips, and thus, if a journey disappeared between D-7 and D-3, it can only be inferred that all available seats have been booked.

The accuracy of the first assumption could not be verified using the data. However, it is generally uncommon for drivers to decrease the number of available seats once a trip has been posted online. If a driver needs to accommodate additional luggage, they can stop accepting booking requests once their car is full without having to reduce the advertised trip capacity online. The second assumption was validated using the BlaBlaCar API key, which provided access to the total number of trips that were already fully booked on each route. By comparing this variable to the number of instances where a journey disappeared between two data collection points, the accuracy of the data could be determined.

After reshaping the dataset to the transaction level, the last observed price and overall trip details were used. For instance, if the transaction occurred between D-7 and D-3, the price reported at D-7 was considered. This approach was necessary to anticipate cases where a journey disappeared between D-7 and D-3, for which information on D-3 prices was unavailable.

A few remaining duplicated transactions had to be addressed, where the same trip was reported under two different routes, provided that the pick-up/drop-off points were within 20 km of both neighboring cities, as per data cleaning step 1. This situation occurred for some routes involving an airport, such as Paris-Nice and Paris-Nice Airport. Assuming that the transactions that occurred on both routes would be erroneous, only the transaction with the smallest average pick-up and drop-off distance to city centers was used. For example, if the drop-off point was near the airport but within 20 km of Nice city center, it was assumed that the transaction occurred for Paris-Nice Airport and the Paris-Nice city center observation would be dropped.

Cases where multiple portions of the same trip are reported were addressed. For instance, if there was a Paris–Marseille–Toulon trip, a transaction specific to Paris-Toulon would imply three observations in the transaction–level dataset. For those cases, the longest portion of the trip was used, i.e., Paris–Toulon and the intermediate ones, *i.e.*, Paris–Marseille and Marseille–Toulon were dropped.

Hence, this cleaning approach enabled the constituting of a large dataset of BlaBlaCar transactions, while only using prices of listed trips that were eventually booked. The number of BlaBlaCar transactions across our routes of interest is provided in Table 2. Map illustrations are provided in Figure 2, which report the number of trips on each city pair, aggregating the number of transactions that occurred in both directions of the route.[19]

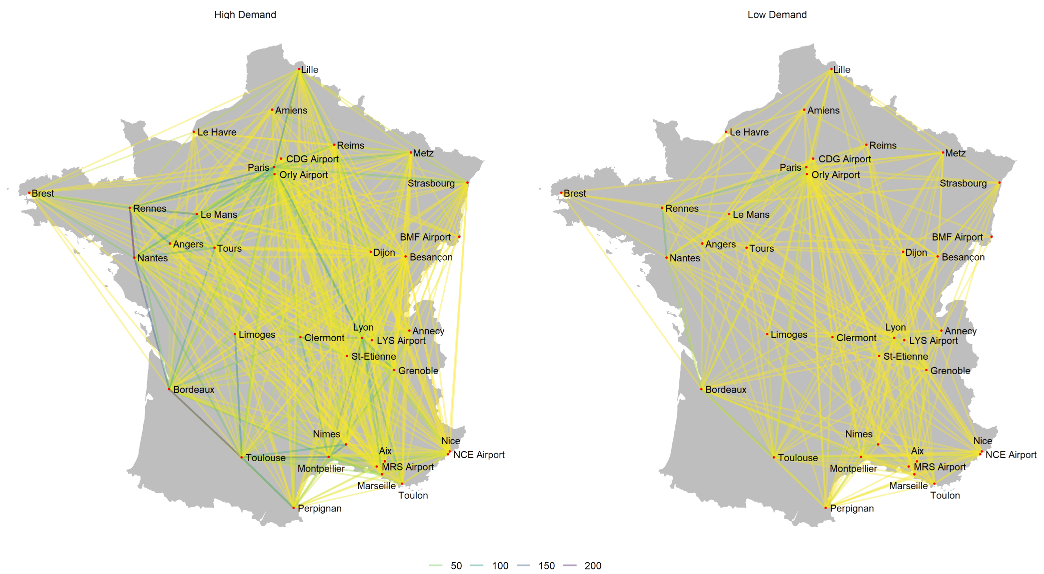

Figure 2: Carpooling number of trips - High (l.) and Low demand (r.)

The Nantes–Rennes route (in both directions) had the highest number of transactions on both the 2nd January and 24th January 2022 datasets, with 211 and 61 transactions, respectively. Bordeaux–Toulouse and Bordeaux–Nantes completed the top three carpooling passenger volumes for the 2nd January 2022 dataset, while Paris–Rennes and Bordeaux–Toulouse were 2nd and 3rd in the 24th January 2022 dataset. The maps also illustrate that most city pairs had small transaction numbers.

4.2.2 The *Comparabus* dataset

Various cleaning steps were conducted on the raw data collected from Comparabus. All coach and train trips where prices were absent or zero were removed. All train journeys labeled as “OUIGO” were removed since they also appear as operated by “SNCF,” resulting in duplications. Consequently, only the trips provided by “SNCF” were retained. Duplicated observations were omitted, especially FlixBus journeys that appeared twice on Comparabus but only once on the operator’s website. A few observations that operated by “Movelia” and “Alsa” were combined since they were run by the same company.

The Comparabus data was transformed into a wide format with one row per supplied trip. This approach enabled the merging of the D-7, D-3, and D-1 datasets and analysis of how prices may vary as the departure date approaches. Unlike BlaBlaCar journeys, nearly all coach and train journeys listed had passengers, which obviated the need to

[19] Additional information on cross-border routes are provided in Figure 7 in the Appendix A.

Table 2: Number of transactions (BlaBlaCar data) or Number of trips supplied (Comparabus data) – Results of the cleaning strategy

High demand	***Departure on January, 2^{nd}, 2022***		
Transaction between	Carpooling	Coach	Train
D-7 and D-3	3,337	5,870	4,311
D-3 and D-1	4,838		
Low demand	***Departure on January, 24^{th}, 2022***		
Transaction between	Carpooling	Coach	Train
D-7 and D-3	612	2,913	8,379
D-3 and D-1	1,244		

reshape the dataset at a transaction level. The observed prices are the prices at which transactions occurred, which was not always the case for BlaBlaCar-listed trips. Following these cleaning steps, Table 2 provides the number of supplied trips across the coach and train dataset routes of interest. For the coach mode, Figure 3 shows map illustrations of the number of trips on each city pair, aggregating the number of coach trips supplied that occurred in both directions of the route.

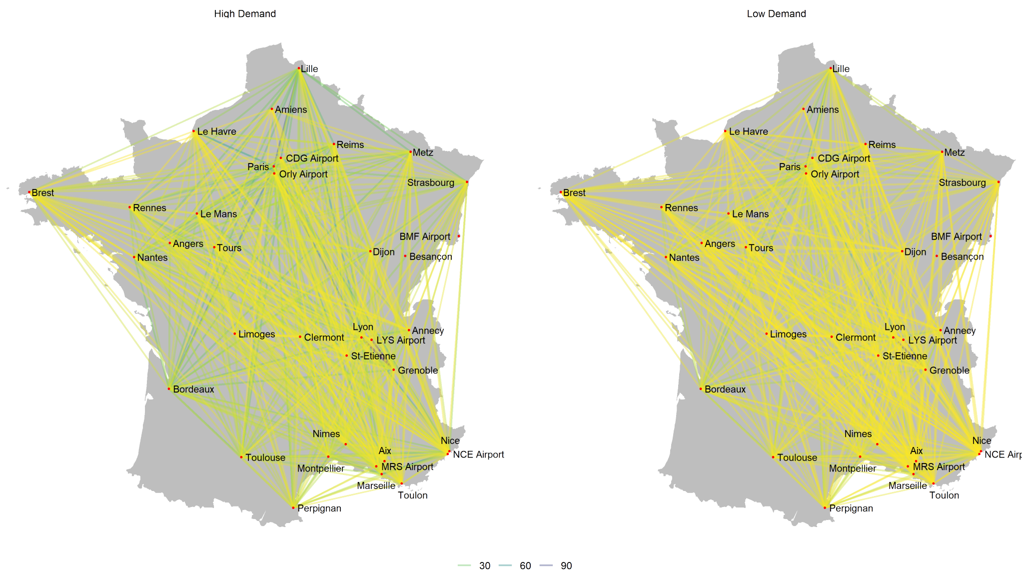

Figure 3: Coach number of trips supplied - High (l.) and Low demand (r.)

The city pairs with the highest daily departures in both directions during times of high and low demand are Grenoble–Lyon and Grenoble–Lyon Airport (LYS), with 114 and 106 trips, respectively, supplied on January 2nd, 2022, and a further 100 and 81 trips, respectively, on January 24th, 2022. Paris also serves as a crucial hub for coach transportation, with three of the top five routes during high-demand weekends involving Paris: Paris–Lille, Paris–Lyon, and Paris–Bordeaux. However, for the January 24th, 2022 data, Clermont–Lyon replaced Paris–Bordeaux in the top five city pairs with the highest departures in both directions.

For the train mode, Figure 4 provides maps illustrating the number of trips on each city pair, aggregating the number of train trips supplied that occurred in both directions of the route.[20]

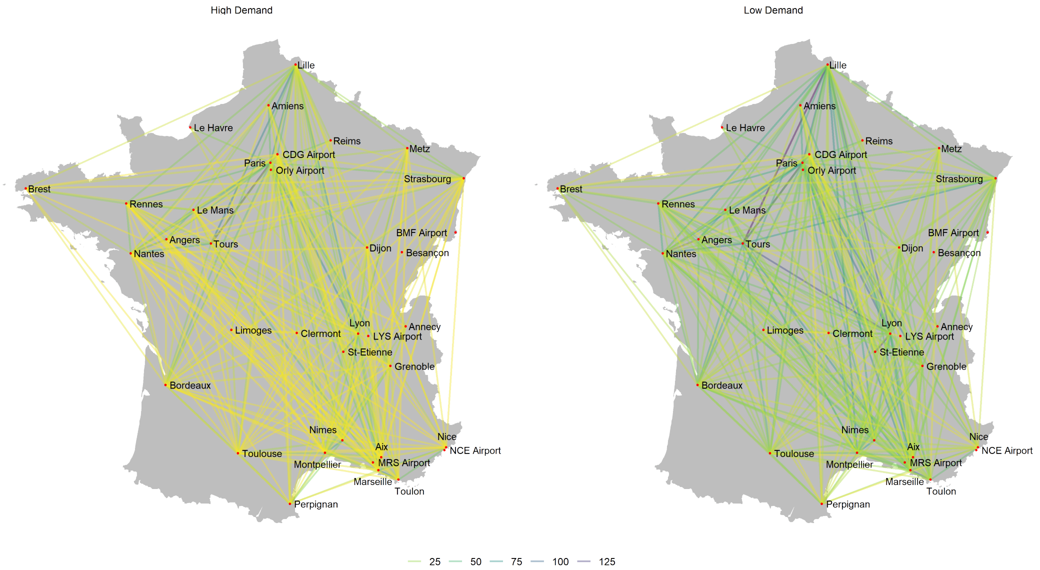

Figure 4: Train number of trips supplied - High (l.) and Low demand (r.)

These maps illustrate important train travel routes between city pairs. Paris emerges as a key transportation hub, as three out of the top five city pairs with the highest demand for train travel during the weekend involve Paris: Paris–Tours, Paris–Lyon, and Paris–Lille. This finding is expected given that most high-speed train lines, known as “TGVs,” connect Paris to other important cities across France. On the low demand Monday dataset, three out of the top five city pairs with the largest number of trips supplied involve Tours, with routes to and from Lille, Paris, and Lyon.

4.3 Defining the carpooling price variable

Prior to examining the determinants of carpooling prices, it is necessary to define the most appropriate price variable to be used in the analysis. To this end, a correlation analysis was initially conducted to explore the relationship between gross prices, trip distances, and durations (Table 3). As expected, gross carpooling prices demonstrate a strong and significant correlation for both distance and duration of trips. This relationship can be attributed to the fact that costs incurred by drivers increase with trip length due to greater fuel consumption. As noted in the previous section (Section 3), the primary aim of carpooling is to offset the cost of car travel. Thus, the strong correlation observed between price and trip length is expected.

Nonetheless, it is important to isolate the length effect of carpooling prices when examining the direct effects of other variables. For example, a higher average price for trips

[20] Data on trips by intercity coach and train extracted from Comparabus does not contain information regarding whether the journey continued or started in another country.

Table 3: Carpooling Gross Prices - Correlation with Trip Distance and Duration

ρ	Carpooling Gross Price		
$[H_0 : \rho = 0]$	High Demand	Low Demand	Pooled Periods
Trip Distance	0.929***	0.927***	0.927***
Trip Duration	0.922***	0.937***	0.921***

Note: *** $p < 0.01$

between 11 p.m. and 6 a.m. may not necessarily indicate that driving at night increases prices, as such trips tend to be longer than daytime trips. Therefore, it is necessary to examine the price per minute or per kilometer to draw more robust conclusions.

To do so, we plot the distributions of prices per minute and per kilometer (see Figure 5). One can observe that the distribution of prices per minute peaks around certain values (e.g., €0.10/min, €0.12/min, €0.125/min., €0.13/min, €0.15/min.), while the distribution of prices per kilometer does not exhibit such peaks.

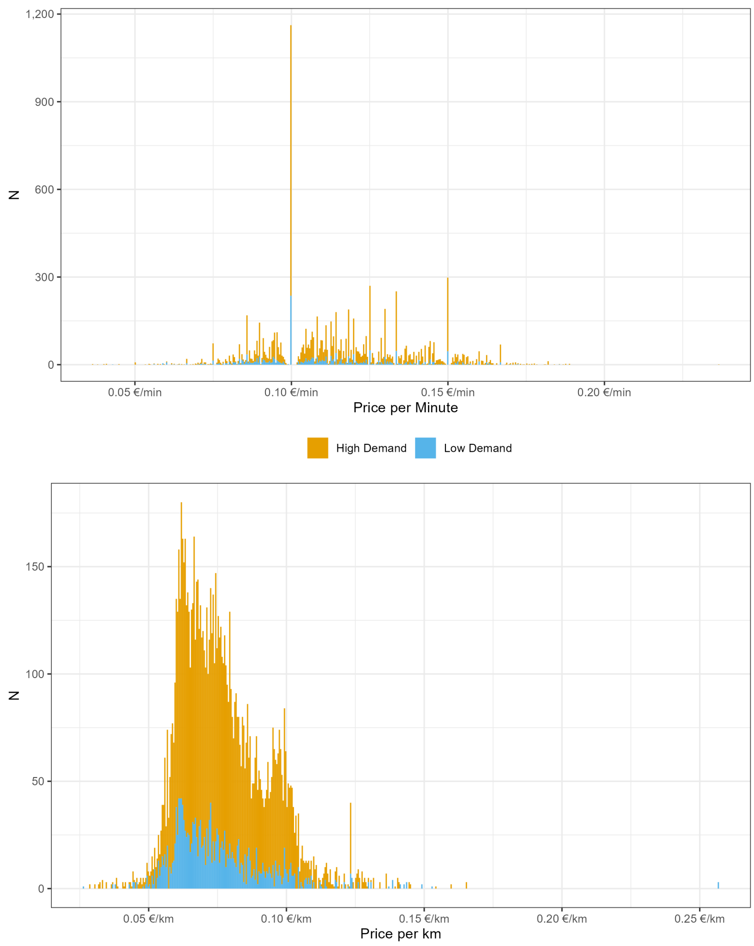

Figure 5: Distribution of Price per Minute and Price per Kilometer

Furthermore, when investigating the determinants of carpooling prices, it is appropriate to consider the price per minute, as it aligns with the notion that prices are driven by costs. If two routes have the same distance but one is easily accessible via a motorway and the other is poorly connected, one would expect different prices. Thus, trip duration, and therefore price per minute, is expected to correlate with cost and prices rather than distance.[21]

While there is limited research on carpooling prices per minute, this measure may become more prevalent in the future due to the emergence of new modes of transportation, such as carsharing[22] services and electric vehicle charging stations. Carsharing services that charge by the minute or by the hour, as well as some EV charging stations for certain operators, have implemented pricing based on time rather than distance or KW (see González et al. (2021) and Bian et al. (2019)). Furthermore, the acceptability of pricing based on time has been studied in the literature (Sulser, 2021).

As highlighted in Figure 5, several peaks were observed at specific round values (see, for example, the highest peak of observations at €/min 0.10), and only very few observations around these peaks. This allows us to identify two distinct pricing patterns. The first type ("Strategy A" hereafter) exhibits a few significant price peaks without any adjacent values (around 30% of the transactions in Table 4), whereas the second type ("Strategy B" hereafter) distributes prices across the entire possible range without highlighting specific threshold values (70% in Table 4).

Table 4: Sample Descriptive Statistics - Price settings

	High Demand		Low Demand		Pooled Periods		
Strategies	A	B	A	B	All prices	A	B
Frequency (#)	2,419	5,646	579	1,277	9,921	2,998	6,923
Proportion (%)	24.38	56.91	5.84	12.87	100.00	30.22	69.78
Share of Strategy B (%)	70.01		68.80		69.78		
	Average figures						
Gross price (€)	19.03	28.75	16.53	26.65	25.40	18.54	28.37
Price per min (€/min)	0.114	0.117	0.112	0.109	0.115	0.114	0.115
Price per km (€/km)	0.077	0.077	0.078	0.074	0.077	0.077	0.077
Trip distance (km)	256	377	224	376	338	250	377
Trip duration (min)	168	248	150	250	223	165	248

These considerations lead to the conclusion that the most appropriate definition of carpooling price is the price per minute. This measure can be analyzed separately depending on whether the pricing behavior aligns with Strategy A, characterized by isolated price peaks, or Strategy B, which reflects a more continuous distribution of prices across the available range.

[21]Recent studies on carpooling choices by users, both drivers and passengers, have shown a high value placed on travel time savings, which is indicative of a significant disutility associated with this form of transportation (see Monchambert (2020); Schmid et al. (2021); Ciari and Axhausen (2012)).

[22]Carsharing is a mobility service that provides users with access to a shared fleet of vehicles for short-term use, typically on a pay-per-use basis. It operates as an alternative to private car ownership, allowing individuals to rent a car for a limited period – often by the minute, hour, or day – through a membership-based or on-demand model.

5 Results

This section presents the results of the statistical and econometric analyses. Factors influencing carpooling prices were investigated by way of graphical and statistical investigations (5.1). Second, several econometric models were investigated, allowing for the explanation of carpooling price determinants (5.2).

5.1 Factors influencing carpooling prices

The extensive data available provides an opportunity to identify the factors that influence the price of carpooling. To do this, the factors were grouped into three broad categories: (i) trip characteristics, (ii) sociodemographic characteristics of the cities, and (iii) level of intermodal competition (i.e., with coach and rail services).

The variables in the first category mainly come from the BlaBlaCar platform, such as trip duration, number of seats purchased, number of transactions, number of stopovers, or whether the trip crosses borders.[23] The sociodemographic category of city pairs includes variables such as population in the departure and arrival cities, average income, and percentage of young people. The last category, intermodal competition, aims to describe the context of competition with other modes of transportation and includes variables such as the number of train trips on the same route on the day, average train fare, and average coach fare.

Descriptive statistics and correlation analyses of each variable are provided below depending on its quantitative or qualitative nature. Trip characteristics impact on carpooling prices were analyzed by exploring all the information collected from the BlaBlaCar website.

Figure 6 illustrates how per-minute carpooling prices vary according to different factors. The analysis shows that the price per minute increases with the number of passengers, resulting in a higher price per person per minute for trips involving multiple passengers. This effect is particularly noticeable when a larger number of seats are booked (e.g., 4 versus 1), and it is more pronounced under Strategy B pricing behavior (see Table 5).

This finding is surprising considering the original intent of carpooling and its regulatory framework, which is cost-sharing among passengers. One might expect that, after the first passenger has booked a seat, the driver would be more likely to cover their cost and decrease their fare (`Hypothesis 1`). However, our inference is that BlaBlaCar drivers do not set prices sequentially and instead charge all the customers the same price.

Unlike traditional transportation services, early booking does not appear to be associated with lower prices, thereby challenging `Hypothesis 6`. In fact, transactions made closer to the departure date are not linked to higher per-minute prices; quite the opposite trend is observed both in the overall sample and within the sub-sample corresponding to Strategy A pricing (see Table 5). In contrast, for Strategy B prices, the timing of the transaction does not significantly affect the price per minute. Instead, prices under this

[23] This is a non-exhaustive list. An exhaustive list of the variables used is provided in Appendix B.

Table 5: Comparisons of price per min across trip characteristics

	Pooled Periods								
	All prices			Strategy A			Strategy B		
	P_1	P_2	$p - value$	P_1	P_2	$p - value$	P_1	P_2	$p - value$
Airport route (y/n)	0.116	0.114	0.002***	0.115	0.114	0.347	0.117	0.115	0.006***
Paris route (y/n)	0.118	0.114	0.000***	0.118	0.113	0.000***	0.118	0.114	0.000***
Crossing borders (y/n)	0.126	0.114	0.000***	0.122	0.113	0.000***	0.127	0.115	0.000***
Automatic booking approval (y/n)	0.113	0.115	0.000***	0.114	0.114	0.854	0.113	0.116	0.000***
Max 2 at the back (y/n)	0.114	0.119	0.000***	0.113	0.116	0.000***	0.114	0.121	0.000***
Women only (y/n)	0.113	0.115	0.729	0.112	0.114	0.748	0.114	0.115	0.826
Seats purchased									
2 vs 1	0.114	0.114	0.764	0.113	0.112	0.480	0.114	0.114	0.960
3 vs 1	0.116	0.114	0.000***	0.116	0.112	0.000***	0.116	0.114	0.059*
4 vs 1	0.122	0.114	0.000***	0.117	0.112	0.003***	0.125	0.114	0.000***
Route with Stopover (y/n)	0.114	0.117	0.000***	0.113	0.115	0.014**	0.114	0.118	0.000***
1 vs 0	0.113	0.117	0.000***	0.111	0.115	0.000***	0.113	0.118	0.000***
2 vs 0	0.113	0.117	0.000***	0.112	0.115	0.001***	0.114	0.118	0.000***
3 and more vs 0	0.115	0.117	0.002***	0.115	0.115	0.933	0.115	0.118	0.000***
Time of the transaction ($D-7/3$ vs $D-3/1$)	0.116	0.114	0.007***	0.115	0.113	0.000***	0.116	0.115	0.234
Time of the trip (Jan. 2 vs Jan. 24)	0.116	0.110	0.000***	0.114	0.112	0.032**	0.117	0.109	0.000***

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

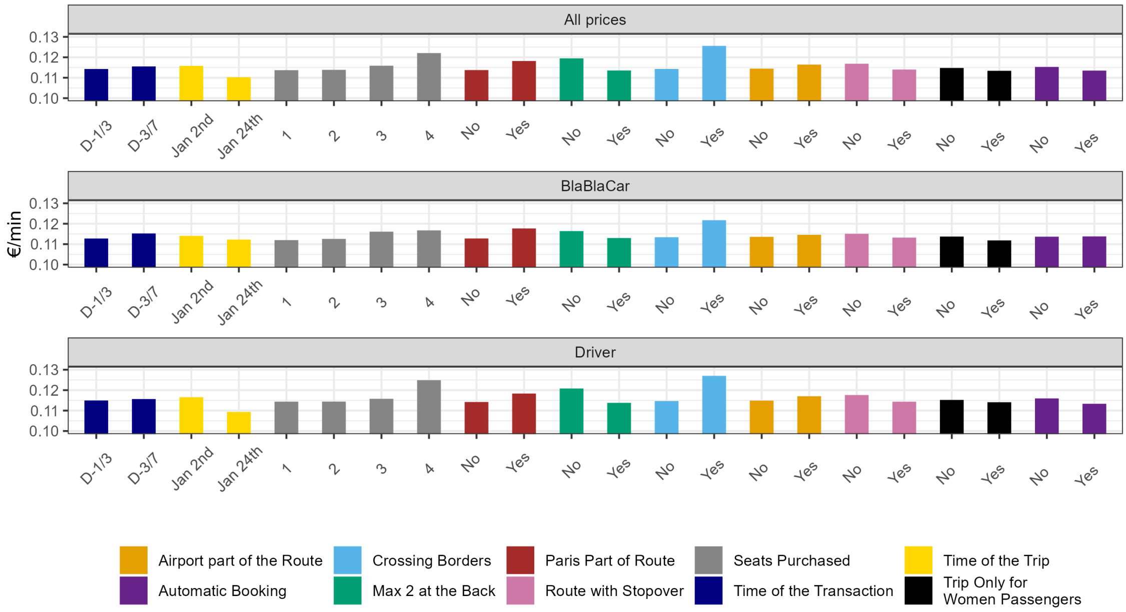

Figure 6: Average Carpooling Price per Min

strategy appear to be more responsive to travel timing - particularly whether the trip occurs during a high - or low-demand period - as confirmed by the figures in Table 5.

Furthermore, journeys that accommodate more than two passengers in the back seat tend to have higher prices per minute, consistent with previous findings. When drivers post their trips on the platform, those who allow more passengers from the outset tend to set higher initial prices on average. Several explanations can account for this pattern.

First, trips allowing more passengers may lead drivers to make additional stops to pick them up. As these trips are consequently listed across multiple route combinations, they gain greater visibility on the platform, increasing the likelihood of being booked. Second, drivers may anticipate selling all available seats and thus feel confident in setting a higher starting price. Third, some passengers may prefer to travel in small groups (three or four people) and may be willing to pay more for that option. In this case, drivers can cater to this sub-market of group travelers with a higher willingness to pay.

In addition, routes with higher demand tend to carry more passengers per car on average, and this pure demand effect across routes also contributes to driving prices upward. The positive correlation between the number of passengers and per-minute price is even more pronounced for trips associated with Strategy B. This suggests that Strategy A pricing is more likely to adhere to the cost-sharing principle at the core of carpooling regulation, while Strategy B may reflect a pricing logic that captures additional surplus from group travelers, thereby approaching a more revenue-oriented behavior.

Figure 6 and Table 5 highlight that cross-border trips have slightly higher prices per minute. This can be attributed to the additional delays that drivers face while crossing a border, particularly considering COVID-19-related restrictions. Moreover, the less intense competition from trains, as high-speed networks are more common within a country, could result in slower trains being used for cross-border journeys, leading to longer trip durations and higher prices per minute. These findings seem to confirm `Hypothesis 3`.

Moreover, the study finds that routes involving an airport tend to have slightly higher per-minute prices compared to those connecting two city centers. However, this effect does not hold for trips associated with Strategy A (see Table 5). These results provide support for `Hypothesis 2`.

Table 6: Correlation between price per min and trip characteristics

	Pooled Periods		
ρ	All prices	Strategy A	Strategy B
Trip distance (km)	-0.022^{**}	-0.079^{***}	-0.021^{*}
Trip duration (min)	-0.064^{***}	-0.095^{***}	-0.073^{***}
Closest departure (min)	-0.042^{***}	0.026	-0.067^{***}
Distance to pick-up (m)	-0.012	0.003	-0.018
Distance from drop-off (m)	0.022	0.003	-0.006
Number of stopovers	0.001	0.057^{***}	-0.017
Number of transactions (on the same route)	-0.018^{*}	-0.044^{**}	-0.002
Speed (km/h)	0.207^{***}	-0.016	0.294^{***}
Trips supplied (on the same route)	0.028^{***}	0.006	0.046^{***}

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

Table 6 further investigates the determinants of per-minute carpooling prices. The analysis reveals a slight decrease in price per minute as trip length increases, whether measured by duration or distance. This negative correlation may reflect a declining marginal cost for drivers over longer journeys. For instance, fuel consumption per minute tends to be lower at higher, more stable speeds—such as those on motorways - due to fewer accelerations and decelerations. However, this interpretation is challenged by the observed positive correlation between average speed and price per minute in the sample. Specifically, higher speeds are associated with higher prices per minute, particularly for trips falling under Strategy B. In contrast, Strategy A prices appear uncorrelated with speed, suggesting different underlying pricing behaviors. Taken together, these findings indicate that drivers applying Strategy B tend to set higher per-minute prices on faster, high-speed routes, while longer-duration trips are generally associated with lower per-minute prices, possibly reflecting economies of scale or a flatter pricing structure over extended distances.

Therefore, it can be noted that carpooling passengers may experience disutility from long journeys and may be willing to pay less while also valuing high-speed journeys. Hence, the willingness to pay for long-duration journeys not connected by a motorway would be the lowest. Conversely, passengers would be willing to pay more for a route involving two relatively near cities connected by a motorway. Therefore, multiple effects need to be controlled for, including route sociodemographic effects, in the analysis carried out in the following sections.

The distance to the pickup or drop-off point does not affect the price per minute. This is initially surprising, as disutility was expected from having to travel far from the city center to be picked up. If a passenger must travel 30 minutes to be picked up, it is expected that their willingness to pay would decrease.

It is noteworthy that the number of stopovers and the price per minute appear uncorrelated (see Table 6). This result is somewhat surprising, as previous research has shown that trip length and speed—both typically correlated with the number of stopovers—have a significant impact on pricing. It is likely that multiple opposing effects are at play, effectively offsetting each other. On the one hand, an increase in stopovers generally leads to longer trip durations, which may reduce passengers' willingness to pay. On the other hand, additional stopovers allow the trip to match a greater number of route searches on the platform, increasing its visibility and booking probability. Anticipating higher demand, drivers may then set higher prices. These two countervailing effects appear to neutralize each other in the aggregate data. However, when isolating trips under Strategy A, the exposure effect seems to prevail. This is consistent with what we refer to as indirect network effects, whereby broader route visibility enhances the likelihood of booking and influences pricing behavior.

This data sheds light on intramodal competition within the carpooling market. The number of trips offered on a given route is positively associated with the price per minute, except for trips following Strategy A, for which no significant effect is observed. Additionally, there is a negative but weakly significant correlation between the price per minute and the number of transactions recorded on a route. Notably, this relationship is more pronounced under Strategy A pricing and becomes statistically insignificant under Strategy B.

We also observe a negative correlation between per-minute prices and the time gap to the closest competing trip, a pattern largely driven by observations associated with Strategy B.

5.2 Econometric analysis of carpooling pricing determinants

This section presents an econometric analysis of the determinants of carpooling prices, with a specific focus on distinguishing between different pricing strategies. It is structured into three subsections. The first subsection discusses methodological considerations and introduces the econometric model used to examine the influence of trip characteristics, sociodemographic factors, and intermodal competition on carpooling prices. The second subsection reports the results for the full sample of trips, while the third compares pricing dynamics across the two distinct pricing patterns–Strategy A and Strategy B.

5.2.1 Methodological issues

As detailed in Section 4.3, utilizing a per-minute price allows for identifying two pricing strategies. This study hypothesizes that these two sub-samples may have distinct price determinants. However, first, the determinants of carpooling prices across all trips (5.2.2) were examined before specifically analyzing the determinants for trips where the price was set using Strategy A, and for those where the price was set using Strategy B (5.2.3).

For each type of trip, an econometric analysis of the determinants of carpooling price per minute was conducted using various sets of explanatory variables. These explanatory variables, detailed in Appendix B, are classified into three main categories: trip characteristics, sociodemographic, and intermodal competition. A log-log regression model[24] with five variants (model (a) to model (e)) was carried out using SAS software.

Models (a) and (b) include only explanatory variables from the trip characteristics category. Model (a) incorporates the standard variables typically used to explain the price of any transport service, such as duration, transaction time, number of seats purchased, trip crossing border, trip from/to airport, number of transactions, trip from/to Paris, and trip on January 24. These variables are represented by the vector TRP_1. Model (b) adds further controls that are specific to the carpooling context, including distance pick-up, distance drop-off, automatic booking approval, max. 2 passengers on backseats, number of stopovers, and women only. These additional variables are represented by the vector TRP_2. Model (c) further incorporates the socio-demographic characteristics of the departure and arrival cities. These variables are represented by the vector SDC.

Models (d) and (e) build upon the previous models by introducing the level of intermodal competition. In model (d), this is done in a preliminary manner using dummy variables that indicate the presence of rail or coach alternatives to carpooling, represented by the vector $COMP_1$. In model (e), intermodal competition is described in more detail, including variables such as average coach duration on the route, average coach price on the route, average train duration on the route, average train price on the route, number of coach departures on the route, and number of train departures on the route. These variables are represented by the vector $COMP_2$. The five models (a) to (e) can be expressed as follows:

$$\begin{aligned}
log(Y_i) &= \alpha_0 + \alpha_1.log(TRP_{1,i}) + \epsilon_i && (1)\\
log(Y_i) &= \alpha_0 + \alpha_1.log(TRP_{1,i}) + \alpha_2.log(TRP_{2,i}) + \epsilon_i && (2)\\
log(Y_i) &= \alpha_0 + \alpha_1.log(TRP_{1,i}) + \alpha_2.log(TRP_{2,i}) + \alpha_3.log(SDC_i) + \epsilon_i && (3)\\
log(Y_i) &= \alpha_0 + \alpha_1.log(TRP_{1,i}) + \alpha_2.log(TRP_{2,i}) + \alpha_3.log(SDC_i) + \alpha_4.COMP_{1,i} + \epsilon_i && (4)\\
log(Y_i) &= \alpha_0 + \alpha_1.log(TRP_{1,i}) + \alpha_2.log(TRP_{2,i}) + \alpha_3.log(SDC_i) + \alpha_5.log(COMP_{2,i}) + \epsilon_i && (5)
\end{aligned}$$

with Y_i representing the price per minute of carpooling for a given observation i. The vectors $TRP_{1,i}$ and $TRP_{2,i}$ represent the explanatory variables from the trip characteristics category, with $TRP_{1,i}$ corresponding to the usual controls and $TRP_{2,i}$ to the additional controls. The vector SDC_i denotes the socio-demographic variables, while $COMP_{1,i}$ and $COMP_{2,i}$ represent the explanatory variables from the intermodal competition category, with $COMP_{1,i}$ referring to a rough description and $COMP_{2,i}$ to a more in-depth description. The coefficients α_i are the parameters to be estimated, and ϵ_i denotes the error term.

[24]Except for dichotomous variables and variables with a natural zero.

The estimation strategy consists of two distinct steps. First, potential multicollinearity issues arising from the large set of explanatory variables necessitate the use of an algorithm for selecting variables with a low variance inflation factor (less than 5). Second, for the variables that meet this condition, models (a) to (e) were estimated using a stepwise selection method based on the Schwarz Bayesian Information Criterion (SBC).

5.2.2 Carpooling price determinants across all trips

The results of the empirical strategy described in section 5.2.1 are provided in Table 11 in Appendix C.

Trip characteristics First, the duration of the trips (measured in logarithmic minutes) plays a crucial role: the longer the trip, the lower the price per minute tends to be. This finding suggests that longer trips benefit from economies of scale, allowing drivers to reduce per-minute costs. Additionally, the number of seats purchased is positively correlated with the price per minute, contrary to the initial expectation (`Hypothesis 1` was not validated). While it was anticipated that an increase in passengers would lead to a decrease in the overall price, in line with the cost-sharing principle of carpooling, it seems this effect is outweighed by the higher willingness-to-pay for groups traveling together.

Interestingly, routes with a higher number of transactions are associated with lower prices, which aligns with `hypothesis 4` regarding the impact of intramodal competition. More transactions likely indicate a more competitive environment, driving prices down as drivers compete for passengers. Furthermore, trips on January 24th, a low-demand day, are priced significantly lower, suggesting that prices decrease during periods of lower demand.

Route characteristics The analysis also highlights the importance of specific route characteristics (models (a) and (b)). For instance, trips crossing borders are consistently priced higher, a finding that supports `hypothesis 3`. This is likely due to the additional costs and complexities associated with cross-border travel, such as longer distances and potential regulatory hurdles. Regarding the airport variable, which captures whether a trip involves a route to or from an airport, the positive and significant coefficient associated with this variable indicates that trips involving airports tend to have higher prices. This finding validates `hypothesis 2`, which suggests that routes connected to high-demand areas like airports command higher prices due to increased demand and potentially higher operational costs. Airports are typically major hubs with a consistent influx of passengers, which could increase the price as demand for transportation to and from these locations remains high. The significance of the airport variable underscores the importance of strategic location in determining carpooling prices.

Passenger comfort strategies The negative and significant coefficient for the Max. 2 passengers on backseats variable suggests that trips where the driver limits the number of backseat passengers to two tend to have lower prices. This finding might seem counter-intuitive at first, as one might expect that offering more space and comfort would allow drivers to charge a premium. However, a plausible explanation is that drivers who impose this limit may be targeting a more budget-conscious market segment. By offering slightly lower prices, these drivers could be appealing to passengers who are price-sensitive but still value the extra comfort of not being crowded in the backseat. This strategy could be particularly effective on shorter trips, where the comfort benefit is appreciated but not enough to justify a significant price increase. Another possibility is that the lower prices reflect a competitive strategy, where drivers, aware that limiting backseat passengers reduces potential earnings, set lower prices to ensure they attract enough passengers to fill the available seats.

Impact of automatic booking approval The automatic booking approval variable offers interesting insights into pricing strategies in the carpooling market (from model (b) onwards). The coefficient for this variable is negative and significant, indicating that trips with automatic booking approval tend to have lower prices. This finding suggests that BlaBlaCar might be using lower prices as an incentive to encourage drivers to enable automatic booking approval. By reducing the price, the platform likely aims to increase the attractiveness of these trips to passengers (indirect network effect), thereby improving the efficiency of the booking process. Automatic booking can streamline operations, reduce booking uncertainties, and ensure that seats are filled more quickly, which benefits both drivers and passengers in the context of two-sided markets. Moreover, the lower prices associated with automatic booking could reflect the platform's strategy to standardize and simplify the booking experience, making it more appealing for users who prioritize convenience and certainty over flexibility. This approach aligns with broader trends in online platforms, where automation and instant confirmation are often incentivized to enhance user experience and operational efficiency.

Demographic influences The inclusion of demographic variables (model (c)) in the analysis provides a richer understanding of the factors influencing carpooling prices. The results show that cities with more developed infrastructure (e.g., more stadiums), wealthier populations (e.g., a higher share of homeowners), and specific socioeconomic characteristics (e.g., the share of divorced individuals or secondary homes) all contribute to the pricing strategies observed in carpooling. These findings suggest that pricing is not only determined by the characteristics of the trip itself but is also significantly influenced by the socioeconomic context of the cities involved, validating the importance of considering these variables in any comprehensive analysis of carpooling prices.

Intermodal competition effects Model (d) introduces intermodal competition variables, revealing significant dynamics in how alternative transportation options impact carpooling prices. The results indicate that competition from coach services has a noticeable impact on carpooling prices by increasing them (`hypothesis 7` was not validated). This effect could be due to market segmentation, where budget-conscious travelers opt for coach services, leaving carpooling for those who are willing to pay more for flexibility, convenience, or comfort. The positive and significant coefficient for log (Number of coach trips on the day/route) in model (e) supports this, suggesting that an increase in coach trips is associated with higher carpooling prices. Moreover, higher average coach fares log (avg. coach fare on the day/route) are also associated with higher carpooling prices, possibly reflecting price signaling or the perceived value of carpooling as a premium alternative. Conversely, the variable log (avg. rail trip duration on the day/route) has a negative and significant coefficient, indicating that longer rail trip durations lead to lower carpooling prices. This result highlights how slower rail services might push passengers towards carpooling, prompting drivers to reduce prices to capture this demand. These findings underscore the complexity of the competitive landscape in transportation, where different modes may not always compete directly but instead complement each other or serve distinct traveler needs.

5.2.3 Determinants of carpooling prices for two identified pricing strategies

In this subsection, we assess the robustness of the previous findings by estimating carpooling prices separately for trips associated with Strategy A and Strategy B. The econometric results, reported in Tables 12 and 13 (Appendix C), correspond to the sub-samples of trips priced under Strategy A and Strategy B, respectively. These estimates reveal notable differences compared to the results in Table 11, which aggregates all trips. Such differences underscore the distinct pricing logics underlying each strategy and their differential responses to market conditions and competitive pressures.

Strategy A The results for Strategy A pricing, presented in Table 12, reveal a distinctive and standardized pricing approach. Prices under this strategy appear to be less responsive to competitive pressures, such as the number of coach services operating on the same route. This suggests a deliberate orientation toward price consistency, potentially designed to offer users a predictable and uniform pricing experience, regardless of market-specific competitive dynamics.

In addition, Strategy A prices display limited sensitivity to sociodemographic characteristics, which are found to significantly influence Strategy B prices. This relative insensitivity may reflect an intent to simplify the pricing structure, avoiding the complexity of adjusting fares based on the characteristics of origin and destination cities. Such an approach likely enhances the usability and perceived fairness by delivering a more transparent and homogeneous pricing framework, independent of local economic disparities.

The variable automatic booking approval is not significant in Strategy A pricing. By contrast, the variable Number of stopovers has a positive impact on the price per minute (models (b) and (d)), suggesting that Strategy A users perceived the interest to stop more often than they initially would by setting higher prices. This strategy perfectly illustrates how important it is for a platform to play on both sides of the market to encourage as many matches as possible.

Interestingly, the number of transactions remains a significant determinant in the Strategy A pricing model, thereby providing support for `Hypothesis 4` and aligning with broader insights from platform economics (Belleflamme and Peitz, 2021). This contrasts with the findings from the Strategy B model (*cf. infra*), where the same variable is not statistically significant. The persistent relevance of transaction volume in Strategy A suggests that overall market activity plays a central role in shaping pricing decisions under this strategy.

Moreover, by emphasizing user satisfaction – notably through lower prices and greater convenience – Strategy A appears to strengthen the network effects that are fundamental to the platform's two-sided market architecture. As more users are attracted to the platform, the perceived value increases symmetrically for both drivers and passengers, reinforcing a virtuous cycle of adoption and engagement.

Strategy B As shown in Table 13, several important trends emerge under Strategy B pricing. Strategy B users appear to exhibit greater sensitivity to competition-related factors. Notably, the positive and significant coefficient for the number of coach services operating on a given route suggests that drivers may respond to increased competition by raising their prices. This behavior likely reflects a strategic attempt to segment the market or to capture demand from passengers who prioritize the flexibility and convenience of carpooling over scheduled coach services, even when the latter are available.

Beyond competition effects, prices under Strategy B are also significantly shaped by the sociodemographic characteristics of both origin and destination cities. For instance, variables such as the number of stadiums or the proportion of divorced individuals in the arrival city are found to influence pricing decisions. These findings suggest that drivers may tailor their pricing strategies according to the local socioeconomic profile, adjusting prices in anticipation of differing demand patterns and willingness-to-pay across urban contexts.

A particularly interesting finding is the continued significance of the max. 2 passengers on backseats variable, which is negatively correlated with price. This indicates that drivers who limit the number of backseat passengers tend to charge lower prices, likely targeting a more budget-conscious segment of passengers who value comfort without a significant price increase. This strategy appears to be particularly effective for attracting passengers on shorter trips, where the comfort benefit is appreciated but not necessarily worth a premium. This finding is in line with that of Farajallah et al. (2019).

Another critical observation is the Distance drop-off (meters) variable, which is not significant in Table 11 but becomes significant with a negative sign in Table 13. This suggests that drivers are more likely to decrease prices as the drop-off distance increases. The negative coefficient implies that drivers might reduce prices for trips that end at locations farther away, possibly as a strategy to attract more passengers by compensating for the additional inconvenience or time required to complete the trip. This indicates that drivers carefully consider the logistical challenges of longer drop-offs and adjust their pricing to remain competitive and appealing to passengers.

Another notable observation is that the variable representing the number of transactions is no longer significant in the Strategy B price model (`hypothesis 4` was not validated). This suggests that drivers may not adjust their pricing based on the frequency of transactions along a particular route. Instead, they might rely more on immediate competitive pressures and localized demand conditions, rather than broader transaction trends across the market. Table 7 summarizes the results of the hypotheses developed in Section 3.4.

Table 7: Summary of hypothesis validation across different strategies

Hypothesis	All Trips	Strategy A	Strategy B
H1 (number of seats)	*no*	*no*	*no*
H2 (airports)	*yes*	*ns*	*yes*
H3 (cross-border)	*yes*	*yes*	*yes*
H4 (intramodal comp.)	*yes*	*yes*	*ns*
H5 (stopovers)	*ns*	*no*	*yes*
H6 (advance booking)	*ns*	*ns*	*ns*
H7 (intermodal comp.)	*no*	*no*	*ns*

Note: 'ns' stands for Non-Significant variable, meaning that the variable is not an influential variable in the model.

Strategic differences The comparison between Strategies A and B highlights the divergent priorities and pricing behaviors adopted by users. Strategy B reflects greater strategic flexibility, with drivers adjusting their prices in response to local competitive pressures and socioeconomic conditions in order to maximize earnings. The insignificance of the number of transactions in this model further suggests that Strategy B drivers are more attuned to immediate, route-specific competition than to broader patterns of platform-wide activity.

A key example of this difference is observed in the distance drop-off variable. For Strategy B, this variable is significant with a negative coefficient, as discussed earlier. This indicates that drivers tend to reduce prices for trips with longer drop-off distances, possibly to attract more passengers by compensating for the inconvenience or additional time required for these trips. This behavior reflects drivers' focus on adapting to the immediate and specific demands of each trip.

In contrast, Strategy A pricing emphasizes consistency, operational efficiency, and user experience. The treatment of the distance drop-off variable under Strategy A further underscores this distinction. While initially insignificant, the variable becomes statistically significant with a positive coefficient in the final model (e), which incorporates the full set of explanatory variables. This result suggests that Strategy A tends to increase prices for trips with longer drop-off distances, potentially reflecting a recognition of the higher perceived value or greater operational effort associated with these journeys. Unlike Strategy B users, who lower prices for such trips to remain competitive, Strategy A appears to apply a standardized pricing adjustment that internalizes these additional costs in a consistent manner. This approach aligns with a broader strategy of offering predictable and transparent pricing, reinforcing the platform's value proposition to users who prioritize clarity and reliability over trip-level optimization.

An interesting finding concerns the influence of the number of stopovers on the price charged. In the full sample (Table 11), the variable Number of Stopovers is not statistically significant, indicating that `Hypothesis 5` is not supported in the aggregate model. This suggests that, in general, intermediate stops do not influence pricing decisions when all carpooling trips are considered together. However, when disaggregating the data by pricing strategy, the number of stopovers becomes an influential variable—but with markedly different effects. For Strategy B users (Table 13), `Hypothesis 5` is validated: the more stopovers between the origin and destination, the lower the price per passenger. This behavior may reflect a strategic attempt by drivers to attract additional passengers by increasing visibility across more route combinations, thereby enhancing the likelihood of filling available seats - even at a lower price. In this context, the number of stopovers is used as a competitive lever to maximize occupancy and remain price-attractive. In contrast, for Strategy A users (Table 12), the relationship is reversed: prices increase with the number of stopovers. This pricing pattern may reflect a perception that additional stops introduce logistical complexity, such as added time, coordination effort, or route deviations, which drivers seek to compensate through higher prices. In this sense, stopovers are treated not as a means to enhance competitiveness, but rather as an added value or service cost that justifies a price premium.

In addition, by maintaining a more uniform pricing structure, Strategy A promotes predictability and simplicity for users, while simultaneously encouraging features such as automatic booking. This approach aligns with a broader emphasis on user satisfaction, whereby strategically lower prices are used to attract a wider user base and strengthen the network effects that underpin the functioning of a two-sided market. Furthermore, the significance of the number of transactions as a determinant of pricing under Strategy A highlights its focus on aggregate market activity. This suggests a pricing logic that remains attentive to overall demand patterns, helping to ensure that prices are both competitive and responsive to platform-wide trends, rather than tailored to highly localized conditions.

Overall, the findings suggest dual strategic orientations in carpooling price-setting. On the one hand, Strategy A users prioritize pricing standardization, platform-wide efficiency, and the reinforcement of network effects, aiming to strike a balance between driver autonomy and a consistent, user-centered experience. On the other hand, Strategy B users exhibit a localized, earnings-driven logic, adjusting prices in response to route-specific demand and supply conditions. These results, in light of the relevant literature (Farajallah et al., 2019; Yeung and Zhu, 2022), suggest that Strategy A might resemble a platform-recommended pricing approach, whereas Strategy B appears closer to driver-set pricing within the range permitted by the platform's recommended price (see Section 3.2). These contrasting approaches reflect different roles that drivers may assume within the carpooling ecosystem, either as flexible micro-entrepreneurs optimizing trip-level revenue, or as platform-aligned participants contributing to long-term service reliability and scalability.

6 Conclusion

This study offers a comprehensive analysis of the determinants of carpooling prices, with particular attention to the heterogeneity of pricing behaviors across two distinct strategies – Strategy A and Strategy B. The findings indicate that variables such as the number of stopovers, route characteristics, trip duration, and competitive dynamics all influence price formation. However, their effects vary considerably depending on the pricing logic employed. Prices set according to Strategy A reflect a more standardized and platform-aligned approach, while those set under Strategy B respond more flexibly to local conditions and individual optimization objectives.

For the full sample, the number of stopovers does not appear to significantly influence pricing, suggesting that, on average, intermediate stops are not a primary determinant of carpooling prices. However, once the data is segmented by pricing strategy, notable differences emerge. Strategy B users tend to lower prices as the number of stopovers increases, potentially leveraging this as a strategy to enhance route visibility and attract additional passengers, thereby maximizing seat occupancy. In contrast, Strategy A users tend to increase prices with more stopovers, likely perceiving them as a source of added complexity, coordination effort, or time costs that justify higher fares. A similar divergence is observed with respect to trip length. Strategy B users tend to reduce prices for longer journeys, possibly reflecting a logic based on economies of scale. Meanwhile, Strategy A users are more likely to maintain or even raise prices for such trips, potentially associating long-distance travel with greater comfort, convenience, or perceived value, thus warranting a price premium.

The results also reveal that intermodal competition, particularly from coach services, affects pricing behavior differently under Strategy A and Strategy B. Strategy A users tend to maintain a consistent pricing structure, prioritizing operational efficiency and user experience over reactive adjustments to local competitive pressures. This suggests a strategy aligned with platform-wide coherence rather than localized revenue optimization. Another key distinction emerges in relation to passenger comfort strategies. Strategy B users who choose to limit the number of backseat passengers tend to charge lower prices, likely appealing to a more price-sensitive clientele by offering improved travel conditions at a reduced cost. In contrast, Strategy A users appear less responsive to this type of variation, indicating that such considerations may be less central to their pricing logic, which remains more standardized across trip configurations.

Despite the rich insights provided by this study, several limitations exist. First, the analysis is constrained by the available data, particularly regarding driver-specific characteristics and individual passenger preferences. Future research could benefit from more granular data, such as drivers' ratings, experience, or real-time demand fluctuations. Such information could offer a more nuanced understanding of the determinants of pricing strategies adopted by both Strategy A and Strategy B users, and allow researchers to better capture the micro-level mechanisms shaping price formation within platform-based mobility markets.

Moreover, the regulatory context of carpooling presents additional avenues for research. As platforms like BlaBlaCar gain market dominance, the balance between flexibility for drivers and pricing consistency for passengers may face increased scrutiny. Regulatory frameworks that aim to maintain fair competition between traditional modes of transport and new platform-based services could shape the future of carpooling pricing strategies. For instance, questions arise regarding the role of price recommendations provided by platforms and whether drivers retain sufficient autonomy under these algorithms.

Lastly, the environmental and social impacts of carpooling—such as its role in reducing carbon emissions or promoting social mobility—could also warrant further investigation. Policymakers may need to consider how pricing models align with broader sustainability goals and how regulations might incentivize carpooling in rural or underserved areas.

In conclusion, while this study sheds light on key determinants of carpooling prices, it also opens the door to deeper inquiries into the evolving dynamics between drivers, platforms, and the regulatory landscape that governs them. Understanding these factors will be essential for fostering a fair and efficient carpooling ecosystem in the future.

Appendices

A Additional maps

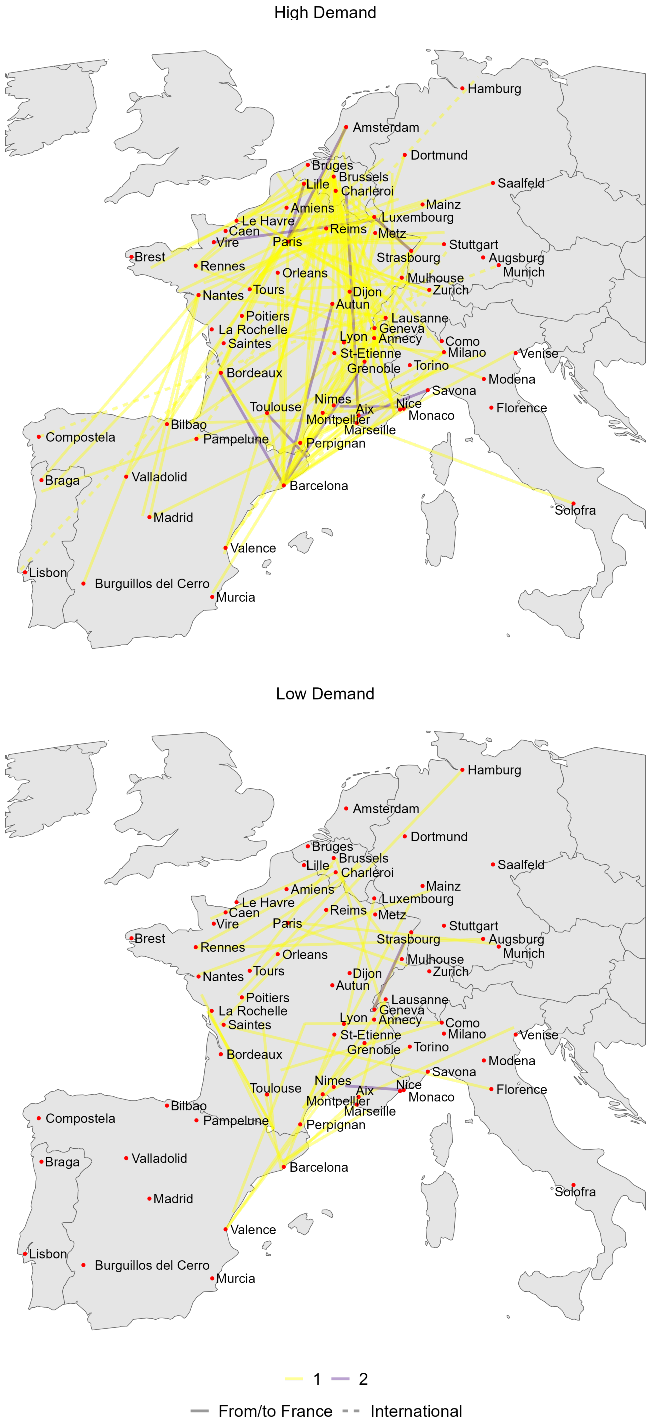

Figure 7: Cross-border routes – High-demand period (top panel) and Low-demand period (bottom panel)

B Exhaustive list of variables

The variables were categorized by type, distinguishing between quantitative and qualitative attributes.

Table 8: List of Trip Characteristics Variables

Quantitative Variables	**Qualitative Variables**
Distance drop-off (meters)	Automatic booking approval
Distance pick-up (meters)	Max. 2 passengers on backseats
Duration (min)	Transaction time (D-7/3 vs D-3/1)
Number of seats purchased	Trip crossing border
Number of stopovers	Trip from/to airport
Number of transactions (on the same route)	Trip from/to Paris
	Trip on January 24
	Women passengers only

Table 9: List of Socio-Demographic Variables
(available for each departure/arrival city)

Quantitative Variables	
Altitude (meters)	No. of general practitioners (‰ inhabitants)
Average income reported to fiscal authorities (€)	Proportion of secondary residences (%)
Proportion of households owning a car (%)	No. of stadiums
Density (Inhabitants per km^2)	No. of swimming pools
Proportion of divorced adults (%)	Proportion of homes occupied by renters (%)
Proportion of single adults (%)	Proportion of vacant housing (%)
Proportion of the population who is female (%)	Proportion of homes occupied by owners (%)
Proportion of the population who is male (%)	Proportion of public housing tenants (%)
Proportion of the population who is immigrant (%)	Proportion of the population who is foreigner (%)
Population of the city	Proportion of manual workers (%)
Proportion of the population above 75 years old (%)	Proportion of the population under 25 years old (%)
Proportion of the working population with executive status (%)	Proportion of people with permanent employment contracts (%)
Surface area (km^2)	Proportion of students (%)
Proportion of people working part-time (%)	Unemployment rate (%)

Table 10: List of Intermodal Competition Variables

Quantitative Variables	**Qualitative Variables**
Average coach duration on the route (min)	Presence of coach services on the route
Average coach price on the route (€)	Presence of train services on the route
Average train duration on the route (min)	
Average train price on the route (€)	
Number of coach departures on the route	
Number of train departures on the route	

C Econometric tables

Table 11: Carpooling price determinants estimation (All prices)

	Models				
	(a)	(b)	(c)	(d)	(e)
Intercept	-2.004***	-1.964***	4.981***	5.135***	3.786***
	(0.025)	(0.025)	(1.054)	(1.055)	(0.930)
log(duration in min.)	-0.033***	-0.034***	-0.033***	-0.033***	
	(0.004)	(0.004)	(0.003)	(0.03)	
log(# of seats purchased)	0.023***	0.019***	0.017***	0.017***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
log(# of transactions)	-0.008***	-0.007***			
	(0.002)	(0.002)			
Trip on Jan. 24	-0.063***	-0.059***	-0.052***	-0.050***	
	(0.006)	(0.006)	(0.005)	(0.005)	
Trip from/to Paris	0.053***	0.053***			
	(0.006)	(0.006)			
Trip from/to Airport	0.022***	0.022***			
	(0.006)	(0.006)			
Trip crossing border	0.086***	0.082***	0.076***	0.077***	0.059***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
Max. 2 passengers on backseats		-0.041***	-0.039***	-0.039***	-0.041***
		(0.005)	(0.005)	(0.005)	(0.006)
Automatic Booking Approval		-0.018***	-0.018***	-0.018***	
		(0.004)	(0.004)	(0.004)	
# of stopovers					
Distance drop off (meters)					
log(% of part time work in dep. city)			-0.183***	-0.188***	-0.227***
			(0.023)	(0.023)	(0.030)
log(% of part time work in arr. city)					-0.131***
					(0.022)
log(Area of the dep. city (km^2))			-0.019***	-0.019***	-0.028***
			(0.005)	(0.005)	(0.006)
log(# of stadium in the dep. city)			0.022***	0.022***	
			(0.003)	(0.003)	
log(# of stadium in the arr. city)			0.024***	0.024***	
			(0.003)	(0.003)	
log(% of female in the dep. city)			-0.757***	-0.772***	-0.961***
			(0.182)	(0.182)	(0.214)
log(% of female in the arr. city)			-1.355***	-1.360***	
			(0.184)	(0.184)	
log(% of foreigners in the dep. city)					0.036***
					(0.012)
log(% of divorced people in the arr. city)			0.205***	0.206***	
			(0.021)	(0.021)	
log(% of vacant dwellings in the dep. city)					-0.061***
					(0.012)
log(% of tenants in the arr. city)			0.164***	0.156***	
			(0.031)	(0.031)	
log(% of second homes in the arr. city)			0.051***	0.049***	
			(0.006)	(0.006)	
Competition with coach services				0.027***	
				(0.009)	
Competition with rail services					
log(# of coach trips on the day/route)					0.014***
					(0.003)
log(avg. coach fare on the day/route)					0.036***
					(0.004)
log(avg. rail trip duration on the day/route)					-0.052***
					(0.005)
R^2	0.035	0.044	0.060	0.061	0.062
Adj. R^2	0.034	0.043	0.059	0.060	0.061
No. obs.	9,921	9,921	9,921	9,921	6,868

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Variables without any associated coefficient are not significant in any model.

Table 12: Carpooling price determinants estimation (Strategy A)

	Models				
	(a)	(b)	(c)	(d)	(e)
Intercept	-1.895***	-1.910***	-1.711***	-1.289***	4.132***
	(0.032)	(0.032)	(0.429)	(0.319)	(1.229)
log(duration in min.)	-0.054***	-0.053***	-0.042***	-0.049***	
	(0.005)	(0.005)	(0.005)	(0.005)	
log(# of seats purchased)	0.028***	0.029***	0.023***	0.022***	0.025***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
log(# of transactions)	-0.016***	-0.016***			
	(0.003)	(0.003)			
Trip on Jan. 24	-0.043***	-0.041***	-0.023***	-0.020***	
	(0.008)	(0.008)	(0.007)	(0.007)	
Trip from/to Paris	0.067***	0.071***	0.043***	0.037***	
	(0.009)	(0.009)	(0.010)	(0.009)	
Trip from/to Airport					
Trip crossing border	0.062***	0.056***	0.057***	0.049***	0.047***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Max. 2 passengers on backseats					
Automatic Booking Approval					
# of stopovers		0.005**		0.005**	
		(0.002)		(0.002)	
Distance drop off (meters)					$3.141E-6$**
					(0.000)
log(% of part time work in dep. city)			-0.163***	-0.252***	-0.303***
			(0.036)	(0.028)	(0.035)
log(% of part time work in arr. city)			-0.224***	-0.221***	-0.254***
			(0.028)	(0.027)	(0.033)
log(Area of the dep. city (km^2))					
log(# of stadium in the dep. city)					
log(# of stadium in the arr. city)					
log(% of female in the dep. city)					-0.932**
					(0.308)
log(% of female in the arr. city)					
log(% of foreigners in the dep. city)			0.054***		0.084***
			(0.016)		(0.017)
log(% of divorced people in the dep. city)			0.157***		
			(0.030)		
log(% of divorced people in the arr. city)					
log(% of vacant dwellings in the dep. city)			-0.080***		-0.077***
			(0.015)		(0.017)
log(% of tenants in the dep. city)			0.145***	0.146***	
			(0.041)	(0.037)	
log(% of HLM in the dep. city)					0.061***
					(0.016)
log(% of HLM in the arr. city)			0.040***		
			(0.011)		
Competition with coach services				0.037***	
				(0.012)	
Competition with rail services					
log(# of coach trips on the day/route)					
log(avg. coach fare on the day/route)					0.017***
					(0.005)
log(avg. rail trip duration on the day/route)					-0.064***
					(0.006)
R^2	0.059	0.062	0.108	0.100	0.157
Adj. R^2	0.057	0.060	0.105	0.097	0.152
No. obs.	2,998	2,998	2,998	2,998	2,210

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Variables without any associated coefficient are not significant in any model.

Table 13: Carpooling price determinants estimation (Strategy B)

	Models				
	(a)	(b)	(c)	(d)	(e)
Intercept	-2.074***	-1.997***	2.112**	2.112***	-1.266***
	(0.027)	(0.027)	(0.889)	(0.889)	(0.335)
log(duration in min.)	-0.023***	-0.024***	-0.028***	-0.028***	
	(0.005)	(0.005)	(0.005)	(0.005)	
log(# of seats purchased)	0.020***				0.021***
	(0.005)				(0.006)
log(# of transactions)					
Trip on Jan. 24	-0.068***	-0.061***	-0.063***	-0.063***	
	(0.006)	(0.006)	(0.006)	(0.006)	
Trip from/to Paris	0.045***	0.043***			
	(0.007)	(0.007)			
Trip from/to Airport	0.027***	0.025***			
	(0.007)	(0.007)			
Trip crossing border	0.097***	0.097***	0.089***	0.089***	0.068***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)
Max. 2 passengers on backseats		-0.051***	-0.048***	-0.048***	-0.048***
		(0.006)	(0.006)	(0.006)	(0.007)
Automatic Booking Approval		-0.026***	-0.027***	-0.027***	-0.024***
		(0.006)	(0.006)	(0.006)	(0.007)
# of stopovers		-0.005***			
		(0.001)			
Distance drop off (meters)			-2.831$E-6$***	-2.831$E-6$***	-2.508$E-6$***
			(0.000)	(0.000)	(0.000)
log(% of part time work in dep. city)					
log(% of part time work in arr. city)			-0.086***	-0.086***	
			(0.026)	(0.026)	
log(Area of the dep. city (km^2))					
log(Altitude of the dep. city (meters))					0.013***
					(0.004)
log(# of stadium in the dep. city)			0.014***	0.014***	
			(0.003)	(0.003)	
log(# of stadium in the arr. city)			0.016***	0.016***	
			(0.003)	(0.003)	
log(% of female in the dep. city)					
log(% of female in the arr. city)			-1.046***	-1.046***	
			(0.219)	(0.219)	
log(% of foreigners in the dep. city)					
log(% of divorced people in the arr. city)					
log(% of vacant dwellings in the arr. city)			0.037***	0.037***	
			(0.011)	(0.011)	
log(% of tenants in the arr. city)					-0.112**
					(0.038)
log(% of second homes in the dep. city)			0.027***	0.027***	
			(0.006)	(0.006)	
log(% of second homes in the arr. city)			0.041***	0.041***	
			(0.007)	(0.007)	
log(# of doctors in the arr. city)			-0.063***	-0.063***	
			(0.019)	(0.019)	
Competition with coach services					
Competition with rail services					
log(# of coach trips on the day/route)					0.029***
					(0.004)
log(avg. coach fare on the day/route)					0.038***
					(0.005)
log(avg. rail trip duration on the day/route)					-0.030***
					(0.007)
R^2	0.034	0.046	0.060	0.060	0.055
Adj. R^2	0.033	0.045	0.059	0.059	0.053
No. obs.	6,923	6,923	6,923	6,923	4,658

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Variables without any associated coefficient are not significant in any model.

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