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GENERAL INTRODUCTION

Individual vehicles are major polluting sources in cities. 56% of CO_2 emission in France comes from individual vehicles (Sarron, Brasseur, Colussi, Druille, & Serre, 2018). Besides pollution, cars also bring other negative externalities such as congestion and noise (Paris is the 16th most congested city in the world). From the urban planning perspective, too many cars on the road also cause pressure on infrastructure design, such as roads and parking spots. The traditional way to expand infrastructure capacity is to build more and wider roads, to create more parking spaces, and so forth. Since the 1980s, researchers and practitioners have been starting to think from the demand side. It may be possible to improve traffic conditions by dispersing traffic flow and decreasing vehicle ownership while keeping the current infrastructure capacity (Ferguson, 1990). One option of traffic demand management is ridesharing. According to the 2008 national survey of transport and mobility, the vehicle occupation rate for work commutes in French major urban areas is only 1.04 for Paris and 1.06 for other cities. The overall vehicle occupation rate in France merely reaches 1.4 (Armoogum et al., 2008). Thus there is a large potential to reduce cars on the road by putting more people in the same car.

Fighting against negative externalities of cars is not the only reason to promote ridesharing. Ridesharing may also serve as a flexible transportation mode, especially for rural areas with limited public transportation reach. As a public service, public transportation modes such as buses and trains should be accessible to everyone. However, as a network industry, investing in infrastructure in low population density areas bears substantial fixed costs. In France, many rural villages are not served by trains. In terms of buses, there may only be a few services during rush hours. For vulnerable people who live in these areas without cars, mobility is a real challenge. 50% of people who are looking to go back to the job market have refused a job or training opportunity because of transportation difficulties (Auxilia, 2013). On the contrary, there is no lack of cars circulating in rural areas that have empty seats. If ridesharing could be developed in these areas, social justice and public service quality would both increase.

Despite the potential environmental and social benefits, ridesharing remains a marginal practice today. Not only because the majority of people do not practice ridesharing regularly, but the public sector has also long only been focusing on the traditional sectors for transportation planning. The situation is changing these days. Firstly, the concept of a "sharing economy" has become widespread in the last decade (Botsman & Rogers, 2010). Residents, especially those who live in developed countries, have started to think of a more sustainable lifestyle instead of a purely consumerist one. Many digital platforms have emerged to facilitate sharing idle objects and capacities, among which ridesharing platforms occupy an essential part. Secondly, the mindset of practitioners have also changed. In France, several articles in law have been passed to facilitate the promotion of ridesharing. Local governments have been initiating more and more ridesharing projects with the aim of integrated transportation planning. Traditional providers have been making strategic moves to not miss opportunities. Ridesharing has come out of the niche market, and we need to understand the sector and its users.

The thesis is comprised of four chapters. The first chapter introduces the ridesharing sector and the way to promote a sustainable ridesharing practice. We start by reviewing the history of ridesharing between strangers, which started in the US during World War II and spread to Europe in the 1990s. From that time till today, several forms of ridesharing initiatives have been tested. We then provide an in-depth analysis of today's ridesharing market. We first categorize the main business models, and then list the representative companies in France under each business model. We find that the different historical initiatives still exist today. Although technological developments have made web-based and algorithm-based matching easier, low-tech matching modes such as meeting points and telephone-based matching may be more suitable for specific cases. In urban areas, people have convenient public transportation access, and ridesharing targets for work commutes and are based on algorithmic matching. In suburban and rural areas where residents are very dependent on cars, ridesharing is introduced as an inexpensive and ecological way to compensate for the lack of public transportation. The matching modes are less technological but more adapted to the local situation. For inter-city trips, ridesharing becomes quite competitive in terms of price and matching quality. Afterwards, we map ridesharing solutions together with other mobility solutions and discuss the relationship among them. We finish the first part of the introductory chapter by discussing the impact of ridesharing.

The second part of the introductory chapter discusses the two levels for promoting a lasting ridesharing practice: the business level and policymaker level. Based on our knowledge of the motivations and barriers of ridesharing participation, we propose to use the nudge method that benefits from behavioral economics findings to tackle specific motivations. We firstly review the emergence of behavioral economics and the principles of the nudge. Next, we explain the reason why the business and policymaker levels should work together for a long-term behavioral change, and how nudges could benefit both levels. We finish by reviewing the ridesharing policy advances in France. With the new mobility law, ridesharing companies will benefit more from policy and financial support.

The second to the fourth chapters contain three empirical papers on two ridesharing platforms. The first two papers are in collaboration with Ecov, a short distance, rural ridesharing service provider. We conduct two field experiments to understand the monetary and prosocial motivations of drivers. The third paper looks at the supply and demand changes of BlaBlaCar, a long-distance ridesharing service provider, during the railway strike in France in 2008, as well as an estimate of the impact on BlaBlaCar's consumer surplus at the national level.

The motivation of the first two papers comes from field observations. Ecov was founded in 2014 with the conviction to democratize ridesharing in suburban and rural areas, where public transportation performs poorly, and vulnerable people suffer from the lack of adapted mobility solutions. The main idea is to build ridesharing meeting points with electronic information boards. Passengers who need a ride come to the meeting point and make a request. The destination will then be shown on the information board(s) located a bit in front of the meeting point. All drivers passing by can see the request and decide whether they wish to pick the passenger up or not, instantaneously and without organizational cost. At the end of the trip, the passenger can give a ticket to the driver. The driver can claim the payment of the ride by logging into the service's website.[1] In 2016, the first meeting points were built in the western suburbs of the Île-de-France region surrounding Paris.

We are grateful to be among the first to test the service and to talk with the earliest users. We discover that only 20% of the drivers claim the monetary reward. Based on our exploratory

[1]Illustrative images of the meeting points and payment tickets are available in the appendix of the papers.

discussions with the drivers, many of them express their willingness to help the passenger and their limited interest in being paid. The context immediately captures our interest with more following-up questions: Is the low money claim rate due to the negligible payment amount compared to the effort expended for the claiming procedure? Would the low claim rate persist if the payment is large enough? How many drivers are motivated by monetary causes, and how many by prosocial causes, and under which circumstances? Would prosocial motivations be crowded out? How could we benefit from monetary and prosocial motivations to promote short-distance ridesharing, a market segment that lacks a viable strategy to scale up? These questions lead us to design and conduct two experiments.

The first experiment is conducted in January and February of 2017. We hire subjects and trained them to make pre-selected ridesharing requests, and to rideshare with the drivers. The objective of using trained passengers is to reduce biases related to passenger behavior during the trip and to help us collect extra contextual information about the trip and the driver.

The experimental stage lasts for five weeks, with the first and the fifth weeks as control weeks and the three weeks in between as treatment weeks. During each week, the hired passengers request trips of a very short distance (5 km) and a moderate distance (20 km). Drivers never see the price on the information board, but the incentives that they receive on the tickets differ each week. In the first (control) week, drivers see normal prices of the trips: 0.45 € for the 5 km trip and 1.80 € for the 20 km trip. In the second week, the prices remain the same, but we offer the drivers the opportunity to donate their earnings to charity as well as cashing out the money themselves. The purpose is to distinguish those who do not cash out the money due to practical reasons from those who do not cash out the money due to prosocial reasons (under which case the latter may choose to donate the money). In the third week, we triple the monetary reward without allowing drivers to donate. Now, the 5 km trip rewards 1.35 € and the 20 km trip rewards 5.40 €. In the fourth week, we maintain the tripled monetary payment while bringing back the donation option. In the fifth week, we go back to the control week, with normal payment and no donation option, in order to check if there is a time effect. Drivers of the two distances are from the same villages, and so share a similar profile. In total, we collect 199 trips, which is a significant number considering the size of the villages.

The result shows that tripling the price increases the cash-out rate for long-distance trips significantly but has no significant effect on short-distance trips. However, offering a donation option has a significant effect on short-distance trips, no matter the payment level, but it could not attract long-distance trip drivers to donate, no matter the payment level. What is especially interesting is that when the payment of the 5 km trip triples, it approaches the normal payment level of the 20 km trip while the money is easier to earn compared to the time cost. Nevertheless, drivers still tend not to claim the money and to donate the amount when the option exists. The behavior seems to be consistent with the trip distance but not with the payments. Drivers tend to be more generous to give up their compensation when the favor that the latter offers is small.

The second experiment follows up on the findings of the first one. It seems that monetary incentives work better when the trip distance is longer. We wish to know at which point the driver reacts to the payments, both in the money claiming stage and in the participation stage. For this experiment, we focus on one trip of 25 km and present two payment levels to drivers: 3 € (the baseline), and 7 € (the high-level treatment).[2] As in the first experiment, we also hire and train passengers to launch requests and to rideshare with drivers. Differing from the first experiment, we show the payment level on the information board so that we can test the selection to participate under each payment level. The donation option is offered on all trips, but this time drivers can choose to split their payment amount between their account and the charity (a dictator game). The experiment takes place in July and August of 2017. In total, 128 trips are conducted with drivers in the same living area.

The result shows that increasing the price from 3 € to 7 € does not influence how drivers behave, either in the participation stage, as measured by the waiting time of passengers, or in the ticket treatment stage, as measured by the payment claim and donation rate and amount. The concern of a higher monetary incentive may self-select more money-oriented drivers that do not hold in this context. The two payment levels attract the same driver profiles. Conforming with the first experiment, most drivers who choose to claim the ticket would claim the entire amount without donating to charity. The payment claim rate is similar under 3 € and 7 € and is similar to the payment claim rate of the tripled price scenario for the 20 km trip in the

[2] We are constrained by the legal regulation of ridesharing payments so we are not able to offer higher amounts.

first experiment (where the price is 5.40 €, i.e. in between these two levels). The donation behavior does not differ significantly either. We conclude that even though the monetary incentive works well for medium distance ridesharing trips when raised to a suitable level, drivers soon become insensitive to higher payment levels. The good news is that the prosocial-oriented drivers will not be crowded out as long as they have the liberty to distribute their earnings. To promote ridesharing adoption to a higher level, we may need other tools than solely adjusting the monetary incentives.

The first two papers explore individual incentives and business-level nudges on ridesharing adoption, which shed light on the combination of using monetary and prosocial motivations for different trip distances. However, as also demonstrated in the results, the effects are limited. There are always suitable drivers who choose not to pick up passengers no matter the incentive level. Policy-level initiatives are needed. The third paper looks at a quasi-experiment that may give insight on the potential effect of ridesharing adoption under a certain policy orientation.

From April to June 2018, the French national railway company (SNCF) goes on a national-level strike to contest governmental reforms. Almost all inter-city train lines are impacted. The strike timetable has been communicated to the public in advance in mid-March. During the three months, the SNCF employees strike every two out of five days, no matter if the strike period covers the weekends or holidays. Facing the shortage of supply, people are obliged to adjust their travel plans, either by canceling or rescheduling their travel or by choosing another travel model, including ridesharing.

We collect data of the largest inter-city ridesharing platform, BlaBlaCar, during the strike period and one month afterwards to measure the ridesharing usage due to the strike. BlaBlaCar shares anonymous trip information on its API, which allows us to source the supply and demand information of representative routes inside France and to trace their daily changes. In total, we source 1.07 million trips of 41 return trips (82 routes in total) that have been released by BlaBlaCar from April to July 2018. We shortlist 78 routes for further analysis.

With this rich dataset, we first calculate the supply and demand changes during the strike. On average, a strike day generates a 7% increase in the number of seats supplied and a 29% increase in the number of seats booked compared to a non-strike day. We also apply a novel approach to estimate the consumer surplus of BlaBlaCar passengers, based on individual-level data. For the initial 78 routes, the consumer surplus is 39,045 € for an average non-strike day, and 46,892 € for an average strike day, an increase of 7,847 €. To calculate a more precise estimation for the whole of France, we include another 159 return trips (318 routes in total) that cover commutes that include smaller cities and between neighboring cities, which complements the initial 78 routes that mainly cover large cities. For the newly included routes, ridesharing data during the strike period is no longer available from the API. To predict consumer surpluses of these routes, we use propensity score matching techniques. We collect data on the trip characteristics and economic statistics of the cities of all routes. Each route will then have an assigned propensity score. The prediction of consumer surpluses of new routes will be based on the consumer surpluses of initial routes that share similar propensity scores. For the entire set of 318 routes, BlaBlaCar generates 79,413 € on an average non-strike day and 97,166 € on an average strike day, an increase of 17,753 €. Our work suggests that inter-city ridesharing could be a flexible substitute for the railway service.

We further take into account other costs than the financial costs for a more comprehensive welfare analysis of ridesharing and train commuting. For individual decision making, we consider both financial and time costs. For societal decision making, we compare the socio-environmental costs of ridesharing and taking trains. Both cases show similar trends. For routes shorter than 250 km, ridesharing could be individually and socially beneficial, while trains are more efficient when the distance is longer than 250 km.

The theoretical contributions of the thesis are three fold. Firstly, the thesis fills in the literature gap of ridesharing by offering three empirical papers using first-hand data of two French ridesharing platforms. Unlike most of the existing research that use questionnaires and interviews to understand users' motivations and behaviors, we benefit from our data access to test real behavioral choices using experiments. Secondly, we combine theories in behavioral economics with empirical tests. This approach is not unknown in many other sectors but is still pioneering in studying transportation, especially ridesharing, e.g. Metcalfe and Dolan (2012) who theorized how behavioral economics could be of benefit to the transportation sector. The first two papers of this thesis provide real-life demonstrations and enrichments of behavioral economics theory. Thirdly, the thesis does not limit itself inside the ridesharing niche. The third paper shows the relationship between the emerging ridesharing and the traditional railway services, which contributes to the understanding of the empirical industrial organization in the transportation sector with a more integrated view.

Another contribution of the thesis is its usage of a variety of pioneering methods: field experiments, large data set collection via automated API sources, and propensity score matching for prediction. We carefully choose these methods to be compatible with the subject matter, with the paucity of data in the ridesharing sector obliging us to search for innovative methods of collection and analysis.

We are fortunate to be supported by a thesis funding for research collaborations with industrial partners to have first-hand information from the field and easy access to data. For a new ridesharing service, conducting field experiments allows us to collect cleaner data. Also, field experiments are more suitable to empirically test monetary and prosocial motivations of drivers rather than surveys or interviews. The drivers' responses under hypothetical situations for a service that they have barely tried may suffer from serious bias.

For the third paper, we choose a mature platform that has abundant usage data. With the API, we could collect massive data at a higher frequency. BlaBlaCar's API is a public source for everyone to use, but the strategy to trace the daily variation of reservations of a representative sample of France is our contribution. This strategy aims to estimate the supply and demand during the national train strike. The strike itself offers a great opportunity for quasi-experimental analysis. We seize this opportunity to rapidly start collecting data, which requires considerable organization and collaboration between the coauthors and the technical team of the Governance and Analytics. We succeed in overcoming the challenges of cleaning and analysing this massive data set.

The thesis also contributes to the methodology of calculating consumer surpluses. The traditional method often uses market equilibrium price and quantity, and the deviations from the equilibrium under shocks to estimate the demand and supply curves. In our case, we can observe individual-level data, which allows us to construct supply and observed transaction curves from first principles. We can then estimate the market demand curve based on the transaction amounts observed at each price level. We also generalise the estimation of the consumer surplus from our sample of France to estimating the consumer surplus for the whole of France. We use two prediction methods. The first is cross-validation to find the most suitable model to predict the consumer surplus of the unobserved routes from API. The second is propensity score matching to assign a propensity score to each route and to predict the consumer surplus of the unobserved routes by matching their scores with observed routes. Prediction methods are used due to the limited data availability in the API and the same calculation methods for the observed routes cannot be used for the unobserved routes.

The thesis also has numerous policy and strategic insights for practitioners. The close collaboration with the industrial partner inspired the first two experiments. The results help the company to understand better their products and their users. The results also help to encourage users themselves to rideshare more. The protocols used in the experiments could also serve for future trials in other rural areas. Policymakers, both municipalities and national transportation regulators, may draw insights from the research about the ridesharing development and user profiles in rural areas. They may also gain awareness of the potential of using behavioral insights and experimental methods to promote ridesharing. The third paper offers ridesharing and railway service providers empirical data on the impact of a train strike on ridesharing, as well as the substitution effects between ridesharing and train commuting. Policymakers could use this research to understand the welfare impact of the strike and of substituting trains by ridesharing, as well as a more global comparison of the welfare impact of ridesharing and of train commuting, which facilitates an integrated understanding of different mobility solutions.

CHAPTER 1

INTRODUCTION: PROMOTING A SUSTAINABLE RIDESHARING PRACTICE

1.1 Ridesharing: What do We Know?

In the last decade, the notion of the sharing economy has moved from its initial niches and has gained attention of the entire society (Botsman & Rogers, 2010). Based on the concept of making better use of idle assets by sharing them with people in need, a sharing economy responds to the increasing need to rethink the consumerist society. New businesses have emerged in various sectors, both for sharing physical goods and intangible assets. Ridesharing is one of the leading concepts in the sharing economy.[1] There exists dozens of ridesharing platforms just for the French market, and the market keeps growing and attracting funds. Ridesharing is a promising concept, not only because of its current popularity, but also because of its potential to contribute to better overall mobility, as it is a sector of great public concern and brings together many traditional stake holders.

In the first part of this introductory chapter, we give a brief overview of the state of the art of the ridesharing sector. We start by reviewing the history of ridesharing, how it first emerged in the US during war time and developed for many decades, before appearing in Europe. We then categorize the main ridesharing business models today. These business models differ according to territories that services operate in and the types of trips. Ridesharing does not function for all regions or for all trips. The business models converge into three main types, which recall the historical ridesharing solutions. Afterwards, we match the main ridesharing solutions in France with each business model type, and map them with other mobility solutions to demonstrate the

[1]Ridesharing lacks a widely accepted definition among researchers. Some researchers include ride-hailing platforms such as Uber into the definition of ridesharing as ridesharing solutions are often based on similar platforms (Kim, Baek, & Lee, 2018). Others extend the rideshare to non-private vehicles which includes some carsharing platforms (Furuhata et al., 2013). In this thesis, we adopt a narrow definition of ridesharing which is well-defined by the French Transportation Law, article L. 3132-1 approved on 17 August 2015: "The joint use of a land motor vehicle by a driver and one or more passengers, on a non-market basis in which payments are limited to cost-sharing, within the framework of a journey that the driver makes for his/her personal requirements." *(L'utilisation en commun d'un véhicule terrestre à moteur par un conducteur et un ou plusieurs passagers, effectuée à titre non onéreux, excepté le partage des frais, dans le cadre d'un déplacement que le conducteur effectue pour son propre compte.)*

complementary role of ridesharing. We conclude by analyzing the impact of ridesharing.

1.1.1 Emergence and Development of Ridesharing: From US to Europe

Ridesharing is not an arbitrary concept. It is a natural act to offer a ride to family members and friends. However, scaled-up ridesharing with people outside the small social circle appeared much later. Chan and Shaheen (2012) reviewed the history of ridesharing in the US. As a country that is largely dependent on private motor vehicles, the ups and downs of ridesharing are closely related to the economic and political situation, and the government often plays a role. During World War II, ridesharing first appeared in its organized form since cars are precious resources during wartime. The US government required ridesharing arrangements to be made for work commutes for people living in the same neighborhood. Ideally, there should be four people in the same car. Besides companies and factories where ridesharing was mandatory, other institutions like churches and parent-teacher associations were also mobilized voluntarily to arrange rideshares.

After the war, ridesharing in the US witnessed another boom during the 1970s when the energy crisis and the OPEC oil embargo hit the country. Before the crisis, some employers had already started managing ridesharing with the purpose to reduce congestion and to cope with the limited parking lots. The government became inspired by the initiative and launched the employer-sponsored ridesharing program as a strategic response to the energy crisis. At the same time, other ridesharing initiatives were tested, including the first HOV (High-Occupancy Vehicle) lane near Washington, D.C., and three slug lines in D.C.; Houston, Texas; and the Bay Area, California. An HOV lane is reserved for cars with at least two or three people inside (including the driver, often called HOV 2+ or HOV 3+) to offer a faster, less-congested service to those who rideshare. This initiative was then experimented in various states in the US and has been adopted in many countries in the world, including but not limited to Canada, the Netherlands, Spain, Australia, Indonesia, and China. However, HOV lanes are criticized for their effectiveness, which is context-dependent. In research that evaluates the Californian HOV system, researchers found that HOV lanes are underutilized, slower than expected, while only offer a slight improvement in travel time and congestion (Kwon & Varaiya, 2008). Regulation is also a concern, with evidence in several countries that people cheat to be able to drive in an HOV lane.[2]

In contrast to HOV lanes, carpooling lines are conventional routes where people rideshare spontaneously. They emerged in areas where many people share a similar work commute itinerary. This itinerary often involves highways to the destination to be clear so that the journey be time-saving. Pick-up and drop-off locations are informally decided by the community, often at the entrances and exits of highways. Money exchange is hand in hand after each ride, without the need for a centralized platform to manage transactions. As more and more people join the community, these informal conventions spread and consolidate.[3] Carpooling could only exist when several criteria are satisfied: dense employment zones, homogeneous work commutes, agreed meeting points, a potential passenger base, and significant time and/or monetary benefits. Even if these criteria are satisfied, carpooling is not guaranteed to emerge spontaneously. The success of the US slug lines may be the continuation of the ridesharing boom in the 1970s. Shaheen, Chan, and Gaynor (2016) offers an excellent overview of the profiles and motivations of carpoolers in the Bay Area.

In the 1980s and onwards, ridesharing lost its popularity due to the decrease of oil prices. At the same time, the organization of ridesharing evolved towards a more technological path, with the emergence of the first telephoned- and internet-based ridesharing platforms. At this infant stage, the matching was slow, inefficient, and costly, but it indicated the path towards building more efficient platforms later on. Another change was that matching was done between individuals instead of being organized by employers or other institutions, which enlarges the matching pool and refines the matching level.

Meanwhile, in Europe, ridesharing only began to develop in the 1990s, facilitated by increased information exchange and infrastructural access. For example, Belgium built a national database for companies to organize work commute rideshares. The Netherlands also invested in a national campaign of ridesharing information exchange. In France, organized, nationwide ridesharing started during the 1995 public transportation strike (Ballet & Clavel, 2007).

[2] An example is the so-called "car jockey" phenomenon in Indonesia, where some people are paid to fill the empty seats in the cars of solo drivers. https://www.theguardian.com/world/2016/apr/04/end-of-the-road-jakartas-passengers-for-hire-targeted-by-carpooling-crackdown

[3] An example would be a dedicated online forum for carpooling: http://www.slug-lines.com/forum2/default.asp

At the beginning of 1997, the European Union launched the ICARO (Increase of CAR Occupancy) program with financial support, which boosted several experiments in infrastructure. In Switzerland, several parking lots have been reserved for high occupancy vehicles. In the UK, a route has been reserved for buses, bicycles, and ridesharing vehicles. In Austria and Spain, the first HOV lanes have been built (Ballet & Clavel, 2007).

At the beginning of the 2000s, amateur ridesharing websites became more widepsread as the Internet became more and more accessible. This time, the US and Europe developed at the same pace. In France, as of 2007, 43% of the ridesharing services were run by associations, and only 8% were run by businesses (Ballet & Clavel, 2007). The loose management of these websites fragmented the market, and endangered their own viability. So many of them have not survived. These amateur websites work better for long-distance trips, for which drivers and passengers are more flexible in arranging rideshares in advance. Short-distance trips are more spontaneous, which makes them more complicated and more costly to plan. Today, digital platforms run by businesses are standardizing the ridesharing practice and are centralizing the market in order to obtain the critical mass of users.

Nonetheless, ridesharing solutions are not limited to digital platforms. Different commuting purposes and different geographical regions require adapted ridesharing forms. For example, slugging is adopted by people working in the Bay Area, although it is the most high-tech place in the world. In some rural or underdeveloped regions, these digital platforms would not reach them, where acquaintance- or telephone-based ridesharing arrangements or even hitchhiking still dominates. Instead of being an obstacle to the development of ridesharing, in parallel with digital ridesharing platforms, entrepreneurs are starting to enter in and to standardize the “low tech" ridesharing market. We may be witnessing another ridesharing boom, this time at the global level, with both the public policy support to solve congestion and environmental challenges, and the wave of entrepreneurship and digitization. In the next subsections, we introduce the main ridesharing business models.

1.1.2 Categorizing Ridesharing Business Models

Previous research have attempted to categorize ridesharing solutions (B. Cohen & Kietzmann, 2014; Furuhata et al., 2013): in the thesis, we adopt a business model perspective. To come up with a successful business model, the entrepreneur needs to surmount the challenge of obtaining the critical mass of users. Ridesharing, like many other sharing economy sectors, matches users of the two sides of the platform. These matchers often benefit from the network effect (Evans & Schmalensee, 2016): the more people who participate, the easier it is for participants to successfully match, and then the more people will join etc. For ridesharing, obtaining a critical mass has different requirements in three aspects.

The first aspect is the population density and the traffic flow of the operational area. They are the base of the potential drivers and passengers. The more the participants are targeted, the more likely that the ridesharing service will attract users, if other conditions hold equal. Intuitively, urban areas have more residents than suburban and rural areas. However, the theoretical pool of users does not ensure the true potential user pool.

The second aspect is the trip type. The trip type highly influences the transaction cost of forming a match, which consists of the monetary cost of the trip, the time cost of forming the match, the uncertainty of matching, and the opportunity cost of alternative transportation modes. Take the example of work commutes versus leisure commutes of the same distance: for the latter, people would be more tolerant of a longer waiting time and the uncertainty of matching, because they are less in a hurry. The success of long-distance ridesharing is also due to the relatively low transaction cost of organizing the trip comparing to the gain of the shared trip, both for drivers and for passengers. The availability of alternative transportation modes in the operational area is crucial. For people living in urban areas with inexpensive and convenient public transportation access, it would be difficult to convert them to rideshare for daily trips compared to people living in rural areas. The core of the business models of short-distance ridesharing and of urban ridesharing is to decrease the transaction cost as much as possible.

The third aspect is the motivations of the potential users. The motivations of ridesharing participants could also work to favor ridesharing rather than alternative options, even under the circumstances where ridesharing is not cost-efficient. It is thus important for the business model to have the adapted incentives to the most salient motivations of the targeted users and trip types. Research on ridesharing motivations are abundant. For example, Shaheen et al. (2016) interview drivers of the Bay Area carpool during their rideshares, while Créno and Cahour (2015) conduct in-depth interviews with carpooling participants. Shaheen, Stocker, and Mundler (2017) exploit survey data in collaboration with BlaBlaCar. In surveys carried out by practitioners, users' motivations and barriers are systematically asked (ADEME, 2015, 2016). Monetary incentives are often tested empirically because of their ease of implementation. Jacobs, Fairbanks, Poche, and Bailey (1982) tests the effectiveness of monetary incentives to form carpooling on university campuses. More recently, Farajallah, Hammond, and Pénard (2019) scrape data from the BlaBlaCar website to analyze drivers' pricing behavior and matching preferences of both sides.[4]

Other research has found similar motivations and barriers of ridesharing. To sum up, the main motivations include to save money and time (for both drivers and passengers), help people in need (for drivers), make the trip less lonely (mainly for drivers), reduce congestion, and improve air quality (for both). The main barriers include both practical barriers such as the lack of participants, too much arrangement, impractical schedules; and psychological barriers such as safety concerns and the uncertainty of waiting times. In general, psychological barriers can be mitigated once people start to participate. However, the relative importance of each motivation and barrier may differ according to different trip types and different territories. For example, money may not be necessary when the driver only participates occasionally for a short trip, but if she takes a passenger every day to work or she drives a passenger for a long trip, then a proper compensation is necessary.

Based on the aspects above, we categorize three main ridesharing types, with similar business models under each type. They are long-distance, pre-arranged ridesharing; app-based urban ridesharing for work commutes; and suburban and rural ridesharing for all trip types.

[4]Meanwhile, we observe an emerging body of research on user behavior from data from ride-hailing platforms like Uber (L. Chen, Mislove, & Wilson, 2015; P. Cohen, Hahn, Hall, Levitt, & Metcalfe, 2016; Cramer & Krueger, 2016).

Long-distance, pre-arranged ridesharing

Long-distance ridesharing often implies traveling from one city to another, from around 50 km up to several hundred-kilometer distances. Such a long trip are often planned days in advance, leaving the possibility for drivers to post trips online and for passengers to book calmly before departure. Economically speaking, drivers also have the incentive to fill in their cars with more passengers to share fuel and toll costs. Compared to the time and energy spent on finding passengers and making small detours, the costs saved by having extra passengers make it still worthwhile, especially when the distance becomes longer. The long distance also makes it highly unlikely to have professional drivers.[5] These characteristics of long-distance ridesharing could explain its early appearance and its well functioning today.

Long-distance ridesharing services first appear during the 2000s as amateur forums. People post offers and requests. Those websites only offer vague filtering by departure time and by route. It is then up to the drivers and passengers to contact each other. Today, the service design remains the same, with improvements in posting and payment convenience, as well as in matching precision. The current market is also more concentrated to fewer platforms with a critical mass to be able to attract a sufficient number of participants.

App-based urban ridesharing for work commutes

Ridesharing services that target urban areas often find the potential in short distance trips. Inside a city, most of the trips will, by default, not be too long. Besides, for long trips, it may be more convenient to rely on public transportation or only to rideshare a part of the trip due to traffic jams and limited parking in urban areas. Unlike long-distance trips, short-distance trips are more spontaneous, thus less likely to be organized in advance, both for drivers and for passengers, which requires ridesharing services to be able to collect and match offers and requests in real-time. The mobile application is the standard technological support for those services. Also, when the geographical scale reduces, the need for precision in pick up and drop

[5] Professional drivers may exist for trips of one hour on very popular routes, but the likelihood of professional drivers dominating long-distance ridesharing practice is tiny. Often, those drivers are "quasi-professional" because their professions require them to drive all day long. For longer distances, it is economically unprofitable to earn a living from taking passengers via ridesharing platforms. If the charged price becomes too high, passengers could always find cheaper offers by non-professional drivers or switch to another transportation mode.

off locations increases, requiring a more advanced matching algorithm and an even larger user base. Even so, trade-offs still need to be made either to make users move to a specific location or to make them wait longer. The high transaction cost of forming a match is the greatest barrier for short-distance ridesharing to succeed. On the driver's side, the final gain under the ridesharing standard would not be enough to compensate for the effort. On the passenger's side, many inexpensive and reliable alternatives are available. If drivers and passengers are blocked by the transaction cost, the platform will have difficulties to attract enough users, the chance of a successful match will be even lower, the transaction cost becomes even higher, thus forcing users to leave the platform, etc. in a vicious circle.

That is why the first and only successful business model that we observe in this market segment is the ride-hailing platforms like Uber and Taxify. To make sure that drivers' efforts are well-compensated, these platforms pay drivers more than their share of the cost per trip. Eventually driving becomes profitable, and drivers stick to the platform to drive professionally. To keep passengers, they pay less than the drivers' earnings corresponding to the quality of service, and the platform subsidizes the difference. The price was really low in the beginning to gain the loyalty of passengers and drivers, and then passengers gradually started to pay more, but still less than a conventional taxi service. There is no clear answer to whether users will remain loyal once the subsidies are removed. Since the platforms do not own the cars, drivers and passengers can switch to another less stable platform any time at little cost. Under price and subsidy competition, the platforms are in no doubt that their operational costs exceed their revenues. The added value is the user travel information that the platforms own. The pricing strategy of these platforms does not comply with the definition of ridesharing that we have adopted. We do not enter into the fierce debate on the positive and negative impacts of these ride-hailing services, as it is out of scope of this thesis. Nevertheless, we would like to highlight the complexity of providing a reliable, non-professional ridesharing service for short-distance trips in urban areas due to transaction costs.

Despite being complex, the urban short-distance market remains an attractive one. Urban areas suffer from being polluted, congested, and a shortage of parking lots. Meanwhile, most drivers keep riding on their own. According to the 2008 national survey of transport and mobility, the vehicle occupation rate in French urban areas for work commutes is only 1.04 for Paris and 1.06 for other cities. The overall vehicle occupation rate in France merely reaches 1.4 (Armoogum et al., 2008). It seems to be a pity to keep wasting empty seats. There are many platforms that are trying to establish themselves in the market without relying on professional drivers. To incentivize non-professional drivers to participate, those platforms offer them an attractive monetary incentive for each ride (often close to the upper-bound of the government-regulated price), even though it may not be as high as for Uber drivers. For passengers, trips are often for free in the beginning. In some cities, trips may be integrated into the local public transportation system. Besides, the platforms place significant efforts to reduce organizational costs. A common technique is to ask drivers to enter their regular trips so that they would not need to re-enter them each time. Over time, platforms start to focus more on work commutes, the most habitual trips of most drivers, and expand to the nearby suburban areas to capture work commutes between suburban and urban areas.[6]

Suburban and rural ridesharing for all trip types

Daily trips inside suburban and rural areas are dramatically different from trips inside urban areas. Firstly, the population density decreases, making it even more difficult to obtain the critical mass for ridesharing platforms. Secondly, residents may be less inclined to use smartphones because of a higher share of aged people, decreased coverage of the 3G/4G network, and a lower purchasing power. Thirdly, public transportation is underdeveloped to satisfy the commute needs, especially during off-peak hours. Considering the population density, it would be unprofitable and environmentally unfriendly to invest in more buses and trains only to have them run nearly empty. People become more reliant on cars, but for those who cannot afford to own a car or those who cannot drive, they become more vulnerable than those living in urban areas. An intuitive solution is to make use of the empty seats in cars and to promote ridesharing. However, the challenge remains to effectively match the spontaneous trips of drivers with the spontaneous needs of passengers in low-density areas. Even though people living in rural

[6]It is always possible to attempt occasional trips during off-peak hours, but there are even fewer offers for the matching to be successful. Platforms competing in this market are focusing their effort on work commutes, although they do not exclude other trip types.

areas may be more willing to spend more time and energy to arrange a trip, it would still be unrealistic to pre-arrange every daily trip. The ridesharing solutions in rural areas should not be too technology-dependent either. Mobile applications as a dominant intermediary in urban areas lose their utility in rural areas.

Although it seems like a niche and challenging market, ridesharing does have a future in nearby suburban and rural areas. People have been sharing rides with friends and families and hitchhiking for a long time. The culture of sharing rides is present, even though the level may differ from one region to another. Local governments are also searching for less costly and more tailored alternatives to public transportation. Ridesharing would be an exciting option to consider.[7] Some local governments experimented with ridesharing solutions in the late 1990s and the 2000s, but not all of them have the capability or the mindset to do so. The first private sector solutions to organize and scale-up suburban and rural ridesharing emerged around 2014. After five years' of development, three main business models stand out. The market is not saturated enough to predict which ones will remain in the future, or whether there is a future for suburban and rural ridesharing, but all three models have a scalability potential, and are unlikely to be dominated by professional drivers.

The first type of solution is similar to the slug lines in the US, mainly in suburban areas for work commutes, not dependent on mobile applications. Instead of waiting for informal meeting points to emerge, official meeting points are proposed with reserved zones. The meeting points are often built close to a highway so that the destination is clear for drivers and passengers. Local communication is ensured by the service operator with the help of the local government to inform people about the existence of the meeting points and the possible destinations. Prices for different trips are imposed. Some services even propose a digitized payment system.[8]

The second type of solution also focuses on work commutes, but among employees who work in the same employment zone, which is isolated from public transportation. Many employees suffer from lack of adapted last-kilometer (or last several kilometers') solutions, while

[7]In a survey run by the ridesharing company Ecov and the LVMT laboratory aimed at low-density municipalities, 98% of the responses consider the local public transportation system to be unsatisfactory. Besides, 96% think that ridesharing could be an excellent solution for work commutes, while the proportion is 82% for all daily trips. The summary of the study (in French) is here: http://www.lvmt.fr/wp-content/uploads/2016/12/CAP_Covoiturage_Synth%C3%A8se_VF_2019.pdf

[8]The payment system may need internet access, but the ride-matching can be done offline.

many others drive alone to work and are frustrated in the middle of traffic jams or in finding a parking spot. There is enormous potential for ridesharing to improve the situation of both groups.

If the above two types of ridesharing are more commonly found in the suburbs with relatively dense residential and employment zones, the third type tries to tackle the challenges faced by rural areas. A typical example is a group of villages which are located in the radius of 30 minutes drive from the closest city with a few hundreds or thousands of residents. The size of the city could vary, but it is the main source for the village residents to find a job, to take a train, or to go to medical appointments etc. In these villages, public transportation is scarce during peak hours and almost nonexistent during off-peak hours. Meanwhile, solo drivers are omnipresent. Unlike suburban trips that are often work commutes, travel needs in rural areas are more spread out during the day. Work commute hours may start earlier in the morning and finish earlier in the evening. Family, administrative, and leisure motives also generate short trips during the day.

Solutions in rural areas propose to scale up short-distance ridesharing in real-time for all purposes for everyone in rural areas. Similar to the carpool meeting points close to the highway, they build physical ridesharing meeting points. Of course, in practice, to make the matching successful, many practical issues need to be solved, from technical ones, such as the location of the meeting point and possible destinations, to operational ones, such as the local communication and the user acquisition.

For people with age, financial, or physical constraints to drive, there exists a ride-hailing service based on the solidarity among residents often organized at the village level. Those who can drive volunteer to drive the those who cannot for the occasional needs of the latter.[9] Passengers call the local coordinator who manages the volunteer driver list to arrange a trip. Drivers will be paid by passengers, but far below the market price for taxi services. The model is similar to the previous telephone-based ridesharing in the US, except that it is a taxi service operated by non-professional drivers dedicated to occasional trips for vulnerable people.

[9] Even though it is not ridesharing to the strict sense, we include this special ride-hailing form here to give a complete picture. The matching pattern is the same as the third-party matching above, and drivers are not profit-driven.

1.1.3 Main Ridesharing Solutions in France

This subsection introduces the categorization, from the previous section, of the main ridesharing services currently operating in France.

For long-distance, pre-arranged ridesharing, the market is dominated by BlaBlaCar. The French unicorn company (i.e. with a market capitalization exceeding 1000 million USD) is created in 2006, after acquiring the amateur platform covoiturage.fr, which itself is created in 2004.[10] BlaBlaCar only allows drivers to post on its website.[11] Passengers search for potential rides by entering the departure city, destination city, and departure time. With increased technical prowess compared to other platforms, their algorithm returns fuzzy matching results, by including offers whose departures or arrivals are close to the searched ones, to enlarge the exact matches.[12] At the same time, the results are ordered by the similarity of matching, making it easier to find the most suitable result. BlaBlaCar allows drivers fix the price as long as it obeys the principle of cost-sharing, and charges a commission for every booked seat. Its success in obtaining a critical mass of users helps BlaBlaCar to maintain its dominance in the French market and to expand to other countries.

Meanwhile, several competing long-distance ridesharing platforms attempt to distinguish themselves from BlaBlaCar in targeted market niches, though none of them can challenge the scale of BlaBlaCar. Mobicoop abandons commission fees to make ridesharing more loyal to its original aims by attracting like-minded users. Platforms like CoviEvent (now also owned by Mobicoop) and Togetzer focus on event-based, ephemeral trips, which can either be long or short distances depending on the type and influence of the event.[13] Some platforms are organized by local authorities to focus on trips in the same region, to facilitate more localised

[10]Many of today's ridesharing operators today evolve from first-generation online forums. iDVROOM, a former SNCF affiliate and now belongs to Klaxit, was created after merging 123envoiture.com and Easycovoiturage. The Finistère *departement*, which created covoiturage-finistere.fr, together with other departements in western France, now allow Ouestgo run their regional ridesharing platform.

[11]It also has a mobile application, but the functionality is the same as the website.

[12]From October 2019, BlaBlaCar also starts matching requests on travel segments. If a passenger's request is a part of a trip that a driver has declared, the passenger will also see that offer according to the new algorithm. Meanwhile, the driver only needs to declare the overall departure and destination without pointing out all the intermediate stops.

[13]We include event-based ridesharing services here even though they may not be of long distance since the business model is the same as long-distance ridesharing, i.e., the offers are available online, rides are pre-arranged and for occasional purposes.

offers and a stronger community spirit: Mov'Ici in the Auvergne Rhône-Alpes, and Ouestgo in the Brittany regions are two examples. Besides inter-city ridesharing inside the region, users can also create community- and event-based ridesharing gatherings. The first part of Table 1.1 lists the representative actors in long-distance, occasional and pre-arranged ridesharing.

BlaBlaLines, launched in May 2017, belongs to the BlaBlaCar group. BlaBlaLines focuses on short-distance work commutes and is only available via its mobile application. The decision to separate BlaBlaCar and BlaBlaLines also shows the different problems faced and strategies adopted by the two market segments. Another main actor in the urban work commute, Klaxit, was created in 2012. The third main competitor, Karos, claims to use artificial intelligence to predict the drivers' itineraries and to assign the most suitable passengers to drivers during their routes. Drivers only need to activate their GPS. For the passenger side, these platforms often propose free rides for passengers during the initial launch of the service. Some remainfree while the others charge no more than 0.1 € per kilometer, which is considerably less than a taxi and could be as attractive as public transit depending on the distance and the subsidy. Ridesharing platforms with non-professional drivers benefit from generous public funding and policy support. Nevertheless, the long-term profitability of ridesharing platforms remains under question, especially for urban ridesharing, where there are inexpensive and convenient alternatives.

For suburban ridesharing that takes the form of slug lines, take the example of LANE in the suburbs of Lyon, the third-largest city in France. There are connected electronic information boards at each meeting point to show drivers the destination of the current request. Drivers could then decide whether or not they need to stop by to pick up the passenger. Drivers could also download the mobile application to be informed about current requests on their route. This option is convenient for those who may need to make a detour to pick up passengers. However, the solution is compatible without using a smartphone, especially for passengers. Another advantage similar to slug lines is that neither drivers or passengers need to organize in advance, which solves the major drawback due to the transaction cost in short-distance ridesharing.

As for ridesharing services for employment zones, the Plateau de Saclay in the southern suburbs of the Paris metropolitan area is a typical example. Several universities, research institutes, and large companies are located in this innovation center, whose conception is ahead of the transportation system planning. From the closest heavy railway station, a traveller needs to take a bus for several stops or to walk for 20-30 minutes to reach the final destination. OuiHop collaborates with companies there to offer ridesharing solutions among employees.[14] It has developed a mobile application for drivers to enter their destinations which can then be matched with the passengers' requests. The driver's itinerary is calculated using geolocation. Trips could be arranged in advance or right before departure.[15] Compared to work commute solutions in urban areas, there is a higher chance that a driver finds a stable ridesharing partner since the user base is more stable. If habitual ridesharing matches decide no longer to use the platform, it may adversely affect the potential participants as the network effect shrinks.

For ridesharing solutions in rural areas based on meeting points, Rezo Pouce and Illicov only offer one destination at each meeting point, while Covoit'ici builds electronic information boards to indicate the destination of the passengers from a list of possible destinations. These meeting points are built in several villages like a bus line. While a bus line is difficult to construct and to satisfy various individual needs, a ridesharing line is based on real-time car traffic and would, in theory, work at any time of the day as long as there are drivers who go to the requested destination.

There exist many self-organized local ride-hailing initiatives to help extremely vulnerable people, under the name of *"transport solidaire"* (solidarity transportation). Les Retz' Chauffeurs, which operates in villages close to Nantes, is a successful example. Many other similar initiatives are too small/local to even have a website. Some times, the local government also takes the responsibility of these services, such as the on-demand solidarity rides proposed by Ouestgo, a ridesharing platform in the Brittany region which operates multiple ridesharing types.

Table 1.1 summarizes the business models of the major ridesharing services in France. Most of them are included in the French governmental ridesharing registry.[16] Services are grouped according to the categorizations above. Besides trip type, trip distance, matching and incentive

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[14]Platforms like BlaBlaLines, Karos and Klaxit are also trying to enter this market segment.

[15]It is possible to organize meeting points at the exit of the heavy railway stations without using a mobile application.

[16]See http://covoiturage.beta.gouv.fr/ for the list. Services in the registry but not included in the list are either because of lack of information or of redundancy with the listed ones.

strategy, the table also presents the operational area and the company or institution that runs the service. We can see a clear convergence of matching modes into two patterns. The first pattern is pre-arranged matching. A web- or mobile-based algorithm proposes a list of potential matches, then drivers and passengers chat and form a ride in advance. In the extreme case of solidarity transportation, the matching process is ensured by a third party. The second pattern is instantaneous matching, usually for suburban and rural ridesharing, based on meeting points. Another observation is that the closer a service is to an urban area, the more digital it becomes. In terms of pricing, due to the government regulation of the cost-sharing principle, the earning of drivers per passenger per kilometer is quite similar across different business models. Passengers either pay for their rides or benefit from subsidies from the platforms themselves or local transport operators. However, there are no free ride shares for long-distance trips.

1.1.4 Mapping French Ridesharing Solutions with Other Mobility Choices

Figure 1.1 maps ridesharing and other mobility solutions of short-distance trips. We roughly divide the space into six blocks. On the horizontal axis, we distinguish three operational areas: trips inside urban areas, trips from suburban to urban areas, and trips inside rural areas or from rural areas to suburban areas. On the vertical axis, we distinguish two trip types: regular trips which are represented by work commutes during peak hours, and occasional trips which include occasional trips for leisure, shopping, administrative and medical reasons, usually during off-peak hours. Inside each block, only the main mobility solutions are presented. We list both solutions that involve motor vehicles and non-motorised solutions such as cycling and walking. We do not distinguish whether the solution is public or private. For ridesharing solutions, we also present the representatives in the French market.

For urban commutes, both work commutes and occasional ones, people often prefer either public transportation options such as subways, trams and buses, or to light, flexible modes such as motorcycles, bicycles and walking. Driving is not very practical in urban areas facing restricted traffic routes, parking shortages and traffic jams. Nevertheless, for those who do drive to work, the solo driver phenomenon is slightly more common than in rural areas. It is where app-based ridesharing platforms like BlaBlaLines, Karos and Klaxit kick in. For the moment,

Table 1.1: Main Ridesharing Service Providers in France and Their Business Models

Solution Name	Belongs To	Created At	Operational Area	Trip Distance	Trip Type	Matching Mode	Matching Timing	Pricing (Driver)	Pricing (Passenger)
BlaBlaCar	BlaBlaCar	2006	France	Long	All types, but mostly occasional commutes	Web or mobile app. Drivers post announcements, and passengers contact drivers through the platform's search algorithm.	Pre-arranged	Decided by drivers but regulated by the platform	Price charged by drivers plus commission
Mobicoop	Mobicoop	2011	France	Short and long	Work commute or daily purposes	Web or mobile app. Passengers and drivers post announcements and contact each other through the website's search algorithm.	Pre-arranged	Decided by drivers	Same as for drivers, no commission
Mov'Ici	Mov'Ici	2016	Auvergne Rhône-Alpes region	Short and medium inside the region	Work commute, event-based or daily purposes	Web or mobile app. Passengers and drivers post announcements and contact each other through the website's search algorithm.	Pre-arranged	Decided by drivers	Same as for drivers, no commission
Ouestgo	Ouestgo	2018	Brittany region	Short and medium inside the region	Work commute, event-based or daily purposes	Web. Passengers and drivers post announcements and contact each other through the website's search algorithm.	Pre-arranged	Decided by drivers	Same as for drivers, no commission
BlablaLines	BlaBlaCar	2017	Urban and suburban areas in France	Short and medium	Work commute	Mobile app only. Passengers and drivers enter their work commutes. The app returns a potential matching list.	Pre-arranged	Decided by the platform according to distance	Freemium
Klaxit	Klaxit	2012	France	Short	Work commute	Mobile app only. Passengers and drivers enter their work commutes. The app returns a potential matching list.	Pre-arranged	Decided by drivers but regulated by the platform, in between 0.07 € and 0.1 € per km	Depends on the region. Either free or 0.1 € per km
Karos	Karos	2014	France	Short	Mostly work commute	Mobile app only. Passengers and drivers enter their work commutes. The app returns a potential matching list.	Pre-arranged and instantaneous	0.1 € per km, 1.5 € minimum per trip	Same as for drivers, no commission
Lane	Ecov	2014	Suburbs of Lyon	Short and medium	Mostly work commute	Meeting points with request shown on a screen and/or sent via mobile notifications to drivers	Instantaneous	Decided by the service and the local government	Free
OuiHop'	Ecov	2015	Suburbs and employment zones in France	Short	Mostly work commutes	Mobile app. Drivers activate the geolocation, enter the destination then receive notifications when a passenger request is close.	Instantaneous	Decided by the service. Drivers gain points that could be used in partnered shops	Free for 3 trips, then 2 € per month
Covoit'ici	Ecov	2014	Several suburbs and rural villages in France	Short and medium	Work commute or daily purposes	Meeting points with request shown on a screen and/or sent via mobile notifications to drivers	Instantaneous	Decided by the service and the local government	Depends on the region. Either free or the same as for drivers
Illicov	La Route Verte	2017	Grenoble and its surroundings	Short and medium	Mostly work commute	Mobile app to declare offer/request and meeting points for matching. Only one possible destination at each meeting point	Instantaneous	Decided by the platform according to distance	Free
Rezo Pouce	Rezo Pouce	2010	Rural areas in France	Short	Work commute or daily purposes	Meeting points with request shown on a screen. Only one possible destination at each meeting point.	Instantaneous	Decided by the platform and the local government	Decided by the platform and the local government
Les Retz' Chauffeurs	Les Retz' Chauffeurs	2015	Rural areas close to Nantes	Short and medium	Daily purposes	Offers and requests are centralized via phone calls or online forms. When there is a request, a coordinator calls potential drivers to form a match	Pre-arranged	0.25 € per km, minimum 3 € per trip	Price per trip plus a 3 € annual membership fee
Ouestgo-solidarity	Ouestgo	2018	Brittany region	Short inside the region	Occasional work commute	Offers and requests are centralized via phone calls or via online forms. When there is a request, a coordinator calls potential drivers to form a match. Each rural area has a coordinator.	Pre-arranged	Voluntary	Free / not specified

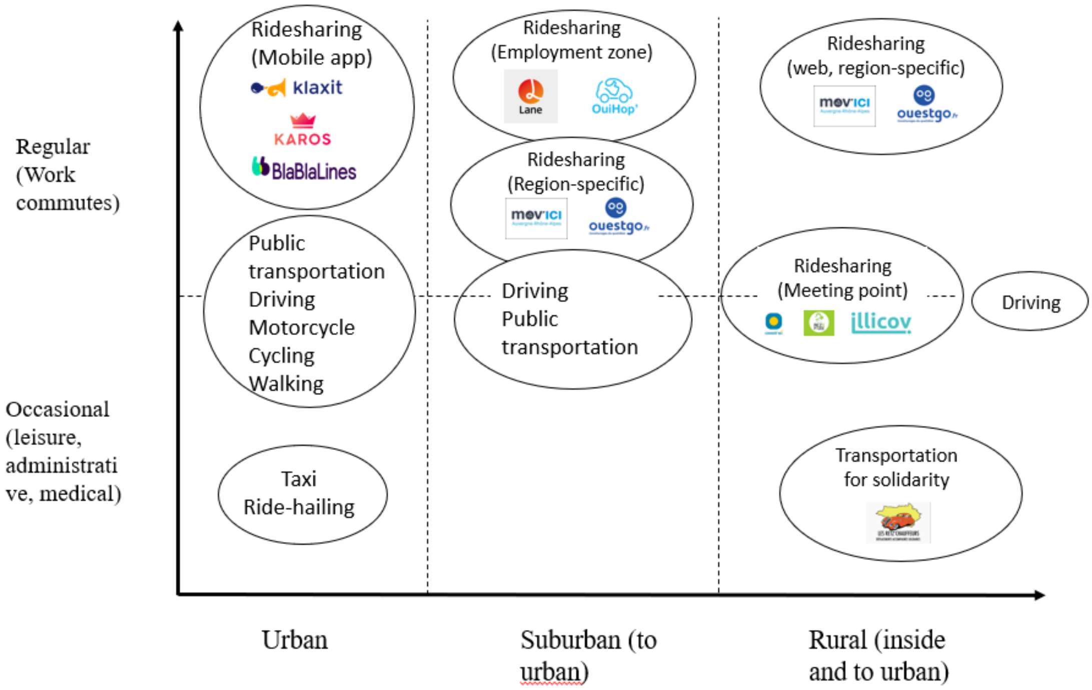

Figure 1.1: Main Mobility Solutions for Short-Distance Trips

they specialize in urban work commutes. In the future, they plan to expand to suburban areas and to occasional trips. For occasional urban trips, people also often prefer taxis and ride-hailing services like Uber.

Once we move outside of the urban areas, public transportation loses its popularity. Whilst trains are still popular for long-distance trips and trips from suburbs to cities, not all routes are served by trains. Inside suburban and rural areas, driving is the default choice of many residents. Several ridesharing solutions have emerged in recent years to tackle the challenges in these areas. For those who specialize in work commutes, we see two main business models. Ridesharing solutions could either be based on pre-arranged trips via web advertisements (often initiated by local governments), or via meeting points alongside itineraries to employment zones. As for occasional trips in suburban and rural areas, which are smaller in volume, less predictable, and geographically more dispersed, ridesharing solutions are still applicable, but barely used in practice. Driving and local public transportation services remain the main mobility solutions.

For rural areas, the main actors converge to the same solution of using meeting points to match passengers with the instantaneous traffic flow for all trip types. Pre-arranged, web-based ridesharing platforms are available but are less practical to use. For extremely rural areas, before the emergence of ridesharing actors, associations for solidarity transportation had already been created to pre-arrange trips by phone. However, this practice, based on volunteers and aimed at highly specific groups of passengers, is difficult to generalize.

In recent years, the French ridesharing market has witnessed a trend of mergers and acquisitions, and a convergence of business models. Several platforms have also changed their names or even legal status. For example, Mobicoop used to be an association when it was created in 2011 under the name of Covoiturage-libre.fr. It switched to a cooperative in 2017. The remaining actors specialize in one market segment but are searching to expand their scope to cover more market segments and to be integrated into the transportation system. A typical example is BlaBlaCar. Already dominating the French market of long-distance ridesharing, it launched its short-distance service, BlaBlaLines, in 2017. In 2018, it also bought Ouibus (now called BlaBlaBus), the long-distance coach service of SNCF (the French railway monopoly) to reinforce its leading market share in long-distance commutes and its ambition to become a transportation solution provider.[17] In 2019, Klaxit also bought iDVROOM, the ridesharing affiliate of SNCF. In the same year, Ecov, the parent company of suburban and rural ridesharing solutions Covoit'ici and Lane, bought OuiHop' to enhance its capacity in real-time geolocation-based matching based. Ecov also manifested its interest in solidarity transportation, with the vision to consolidate the shared experiences of the disparate local initiatives.

The ever-closer connections between the traditional mobility actors and ridesharing companies exist beyond mergers and acquisitions. SNCF has become a minor shareholder of BlaBlaCar since the acquisition of Ouibus. Automobile manufacturers such as Renault, and road infrastructure providers such as Vinci, collaborate closely with ridesharing platforms to offer discounts and subsidies to drivers. Besides financial interests, mobility actors are including ridesharing to extend the reach of their transport offers. SNCF's train search algorithm now also proposes ridesharing results, integrating offers from BlaBlaCar, BlaBlaLines, and Karos.[18]

Ridesharing has become an active actor in the ecosystem of mobility solutions. At the

[17] SNCF's monopolistic position in France will soon end. From the end of 2020, other railway operators can compete in all types of train journeys.

[18] See https://www.deplacementspros.com/transport/lappli-de-la-sncf-integre-le-covoiturage (in French).

current stage, ridesharing has been experimenting to complement the itineraries and schedules that public transportation has difficulties to fulfill. The complementary role is more salient in suburban and rural areas. In the long run, ridesharing has the potential to substitute the need for personal vehicle ownership and ridership. Whether ridesharing can be a substitute for public transportation depends on the region and whether the practice is widely adopted. It is time for policymakers to integrate ridesharing into the overall mobility plan instead of seeing it as a niche market. In the next section, we examine how this can be done and the existing initiatives to facilitate this integration.

1.1.5 The Impact of Ridesharing

Although ridesharing platforms are booming in recent years and that policies are in favor of its development, it remains a marginal practice, since the vehicle occupation rate remains low. There is still a long way to go before ridesharing scales up, but the new French laws facilitate this process. Before examining the scaling-up, we first need to learn about the impact of ridesharing, which is ambiguous in several aspects and needs further clarification.

One of the most important attractions of ridesharing is its environmental benefits. Ridesharing may result in fewer cars on the road as the vehicle occupancy rate increases, lowering the greenhouse gas emission rate because of fewer vehicles $\times$ distance traveled and fewer traffic jams. Transport is the biggest contributor to EU greenhouse gas emissions, generating 27% of emissions (1205 Mt CO_2 equivalent in 2016). Cars and vans contribute around half of these (Todts, 2018). The current method of estimating the potential environmental gains of ridesharing is to compare the difference in the petrol consumption or greenhouse gas emissions of the same population between the current transportation scenario and the rideshare-adopted scenario. Researchers often rely on survey results (national, regional, or service-specific surveys) to learn about the current share of transportation modes and estimate several scenarios of ridesharing adoption levels. They either survey the users of a ridesharing service about their external options had they not rideshared to estimate the CO_2 emissions savings (BlaBlaCar & BIPE, 2019; Minett & Pearce, 2011), or rely on surveys on transportation modes of people and to estimate the CO_2 emissions savings if different percentages of the population start to rideshare (Jacobson & King, 2009). However, the reduction due to the increased ride-sharing in work commutes in France does not seem to be dramatic due to the lack of potential matches. Even in the case where there are four people per vehicle, we would only reduce 6.6% of CO_2 emissions due to work commutes. The rate may reach 16% in urban areas since matching success possibility is higher (Biotteau, 2019).

Furthermore, there is some concern that the benefits of ridesharing will cause a rebound effect. Since driving becomes less expensive and more convenient with ridesharing, people may switch from public transportation to cars, travel longer distances, and possibly move further away from employment zones (Vivanco, Kemp, & van der Voet, 2015). However, this potential rebound effect does not seem to negate the overall positive environmental impact of ridesharing (Yin, Liu, Coulombel, & Viguié, 2018).

Besides the potential environmental benefits, ridesharing is also a more economical way for drivers and passengers to travel. In France, drivers are paid after each shared ride. The price is often in proportion to the distance and the number of passengers, and which is regulated not to surpass the trip cost. If a driver shares a ride with four passengers so that her car is full, and if we ignore the detours, the trip would cost zero to the driver. From the passenger's side, they often benefit from free rideshares, as these are either offered by the company or integrated with local public transportation fares. Even when they need to pay, the cost per shared ride is usually no higher than equivalent public transportation fares for daily commutes. Besides, they could benefit from up to 400 € of subsidies annually from their employers, as the new mobility law requires. For long-distance commutes, passengers could easily find less expensive prices than trains, especially when they need to book in the last minute.

The economic benefits of ridesharing at meso- and macroscopic levels are more difficult to quantify. For automobile manufacturers, in the short run, their sales may drop due to a more efficient use of personal vehicles, though in the long run, they may gain market popularity by collaborating with ridesharing companies. For mobility solution providers, introducing companies that are specialized in ridesharing will certainly bring competition to the market and fill in some market gaps. More competition would, in principle, improve consumer well-being by lowering prices and offering better services. It is more of the case in long-distance ridesharing, where ridesharing is more developed to compete with other transportation modes. For short distance, daily commutes, as ridesharing companies still rely on substantial public and private funding, the long term economic benefits to the sector and to society are difficult to ascertain for the moment. We could not find academic research that measures the competition and well-being impact of ridesharing, though related papers could be found on ride-hailing platforms.[19] The third paper of the thesis tries to measure the well-being impact of long-distance ridesharing platform BlaBlaCar in the context of a national railway system strike.

Ridesharing, especially for rural areas, may also help improve social justice. The most precarious groups in society, non-adults, older people, poor people, and disabled people, are often those who cannot drive and/or are obliged to live far from the center because of lower housing costs. Ridesharing provides them an alternative to the poorly functioning public transportation system to gain access to medical, administrative, educational, and professional services, which often implies several kilometers' trip to a larger town. Having easier access to essential social services not only releases them from their current isolation and vulnerability but also offers them opportunities to exit from their vulnerable situation in the long run. Survey evidence shows that mobility is crucial in job market integration, especially for the precarious population. 50% of those surveyed who are in the early stages of joining the workforce indicated that they had declined job or training opportunities because of transportation problems. 28% of those surveyed even abandoned ongoing employment or training (Auxilia, 2013). On the other hand, improving the socio-economic situation of these vulnerable groups may lead to increased future vehicle purchases and travel, offsetting the environmental benefits of ridesharing.

The benefit of ridesharing to society could be multiplied if it is smoothly integrated with other transportation modes, which is the concept of MAAS (Mobility As A Service). The road infrastructure could be better designed and utilised. Users from urban, suburban and rural areas are better off because they would have a faster and more convenient access to all mobility solutions.

[19] See Hall, Palsson, and Price (2018) on the discussion of the complementarity and substitutability between Uber and public transit, P. Cohen et al. (2016) and Rogers (2015) on the consumer and social welfare impact of Uber.

1.2 Promoting a Sustainable Ridesharing Practice: Business Strategies and Policy Orientations for Behavioral Changes

Now that we know the main motivations for and barriers to participating in ridesharing, the answer to promote ridesharing is to stimulate the motivational aspects and to remove the barriers for potential participants. In this section, we discuss the two levels (business and policymaker) that can be mobilized to promote ridesharing, as well as the underlying behavioral principles of our understanding of the motivations for ridesharing.

1.2.1 Behavioral Intervention at Two Levels

The school of neoclassical economics that has built the mainstream of the discipline of economics as it is today is based on the assumption that human beings are completely rational. That is, they have complete and transitive preferences so that they can maximize their utility function when making each decision. The rationality assumption helps economists to model the complex world in elegant mathematical formulas and to work out the equilibrium solutions. However, it has been challenged since the last few decades by researchers of a new branch of economics, known as behavioral economics. Behavioral economists believe that although the rationality approach can help in seeing the essential picture and drawing the general rules, it lacks the explanatory power in the real world since people often behave to the contrary of the predictions of the rationality axioms from the neoclassical economics orthodoxy. Behavioral economists have been working on identifying the violations of the orthodox assumptions to enrich our understanding of human behavior, by following two major streams of reflection.

Some researchers, lead by Hebert Simon, follow the utility-maximizing approach and claim that additional conditions should be added to the neoclassical orthodoxy (Gigerenzer & Goldstein, 1996; Simon, 1997). Individuals cannot obtain all information and have a limited cognitive capacity in making decisions. Nevertheless, they still try to maximize their utility within a bounded rationality. The bounded rationality stream focuses on refining utility functions with more realistic constraints. An example of bounded rationality is satisficing (Simon, 1956). Instead of considering all the options and choosing the best one, individuals tend to stop at a "good-enough" option. If we include the cost of evaluating choices into the utility maximization formula, satisficing would be a rational principle since the extra utility gain from the "best option" compared to the "good enough" option may not compensate for the extra time and energy costs of continuing the search.

Other researchers obtain their inspiration from psychology and show how factors ignored in rationality models like the environment, framing, timing, and emotion could influence cognition and lead people to behave differently under the same information availability. That is, individuals may not be aware of what would maximize their utility. Even if they are conscious of a better option according to their knowledge, they may fail to choose it because of cognitive constraints. Kahneman and Tversky have pioneered this work (Kahneman & Tversky, 1979). In their seminal book, "Thinking, fast and slow", Kahneman synthesizes their work and develops the prospect theory (Kahneman, 2011). Cases, where people know the utility-maximizing option but fail to take action, are often the trade-off between the heuristic, short-sighted "system 1" and the rational, long-term visioned "system 2". A typical example is that we are all aware of the health benefits of exercise, but the effects are too difficult to visualize immediately, so that we often surrender to the instant, visible lure of staying at home or socializing with friends.

Researchers who follow the spirit of Kahneman and Tversky have subsequently used larger samples and more rigorous methods to enrich the discipline of behavioral economics. Camerer and Loewenstein (2003) and Thaler (2016) write approachable summary papers on the history and development of behavioral economics. Since the context in which individuals make decision matters, it is reasonable to think that changing the context may alter individual decisions, even under the same cognitive abilities and budget constraints. It could be particularly interesting when the current choice is not the best for individual well-being. This is where the idea of the "nudge" comes from. Thaler and Sunstein, in their book of the same title (Thaler & Sunstein, 2009), defined a nudge as follows:

> *"A nudge, as we will use the term, is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting fruit at eye level counts as a nudge. Banning junk food does not." (p. 6)*

The principle behind the nudge is called libertarian paternalism (Thaler & Sunstein, 2003). The design of the choice architecture uses several aspects of the known cognitive biases. A typical example of the nudge, as cited by the authors, is that cafeterias put healthy food like fruits and vegetables at the eye level and hide junk food further away or behind in order to incentivize students to eat more healthily. Students are not banned from eating junk food, but now healthy food is easier to see and to pick up, and junk food costs a bit more effort to obtain, so our "lazy" brain will stay with the status quo and choose the easy one. An empirical trial carried out by Thorndike, Sonnenberg, Riis, Barraclough, and Levy (2012) shows a significant effect of a nudge. However, the effects of the same nudge are context-dependent, as documented in a review paper by Wilson, Buckley, Buckley, and Bogomolova (2016).

Nudges have great application potential, which have already been exploited many times in business and in public policy. Experimenting with nudges in real-life cases also offer opportunities to test the external validity of behavioral theories. Business practitioners test various online and offline communication and marketing techniques to attract customers and to make them loyal. They benefit from behavioral economic findings to design campaigns. For example, now that marketers know that individuals avoid loss more than they prefer to gain, they can directly assign a coupon to customers with a deadline. Consumers would create the idea that "If I don't use the coupon now, I will lose the money I could have saved". The spread of the behavioral science also helps to build a culture of experimentation in business, often called A/B testing, to test different variations of nudges to find the most effective campaign. This creates a positive feedback in a virtuous circle since researchers now have more opportunities to work with business practitioners to implement more rigorous behavioral experiments. The access to comprehensive empirical data enriches the testing and development of theories.[20]

Policymakers are also adopting the idea of using behavioral insights to improve public policies and solve social problems. The UK built its first behavioral insight team in 2010. Several other developed economies followed up and created their own governmental behavioral units. Figure 1.2 maps nudge units in the world.[21] Topics covered by public nudge units are extremely

[20]Big technology firms like Google, Amazon, Facebook, and Uber all have their economist teams, whose missions include designing behavioral-based experiments with real users.

[21]Although France is not marked in the map, it does have a behavioral insight team under the French Public Transformation Unit (DITP), split from the Secretary-General for Government Modernization (SGMAP)

wide, including increasing tax compliance (Kettle, Hernandez, Ruda, & Sanders, 2016), adopting a more environmentally-friendly energy usage (Allcott, 2011), designing a better social welfare system (Madrian & Shea, 2001) and many more. Compared to business practitioners, policymakers often face more complex problems, have less flexibility in personalization, need to think of social justice and inclusiveness, and take a longer time to implement and to evaluate the effectiveness. At the same time, people expect policy nudges to have a long-term impact. For these reasons, they need to be implemented more carefully. A simple change of the choice architecture may not be enough to ensure long-term impact. Helping people build decision-making competencies to align their decisions with long-term well-being is as important. This competency-building approach is called the "boost" (Hertwig & Grüne-Yanoff, 2017). Its implementation often requires years of difficult fieldwork, such as educating people and following up on them. Often it is challenging to implement policy nudges directly. Researchers could benefit from external shocks by treating them as natural experiments. Lessons learned from natural experiments could guide policy evaluation as if similar policies were implemented.

We see here two levels of external intervention using behavioral insights. One is at the business level, where marketers make us adopt the solutions they wish to sell. They typically use several simple, short-term nudges based on customer reactions. They can also personalize interventions at a very refined level. Criticism of business-level behavioral intervention is that marketers may manipulate their customers' cognitive biases to achieve their business objectives, which may not be aligned to their customers' well-being (Beggs, 2016). The other one is at the policy level, where policymakers use behavioral insights as a new policy tool to solve classical social problems. They often combine both nudges and boosts. Criticism of policy level nudges does not apply to the intentions of policymakers to improve the well-being of citizens, but rather on the competence of policymakers, who themselves are human and are biased in many ways, to implement the right policy (Sunstein, 2015). More rigorous pre-examination and post-evaluation of policy-level behavioral interventions are needed.

Both business and policy levels are of interest to ridesharing. As presented in the previous

in 2017. The latter began running behavioral insights projects from 2013 and co-founded an NGO, Nudge-France. More information could be found in the World Bank report: http://documents.worldbank.org/curated/en/710771543609067500/pdf/132610-REVISED-00-COUNTRY-PROFILES-dig.pdf

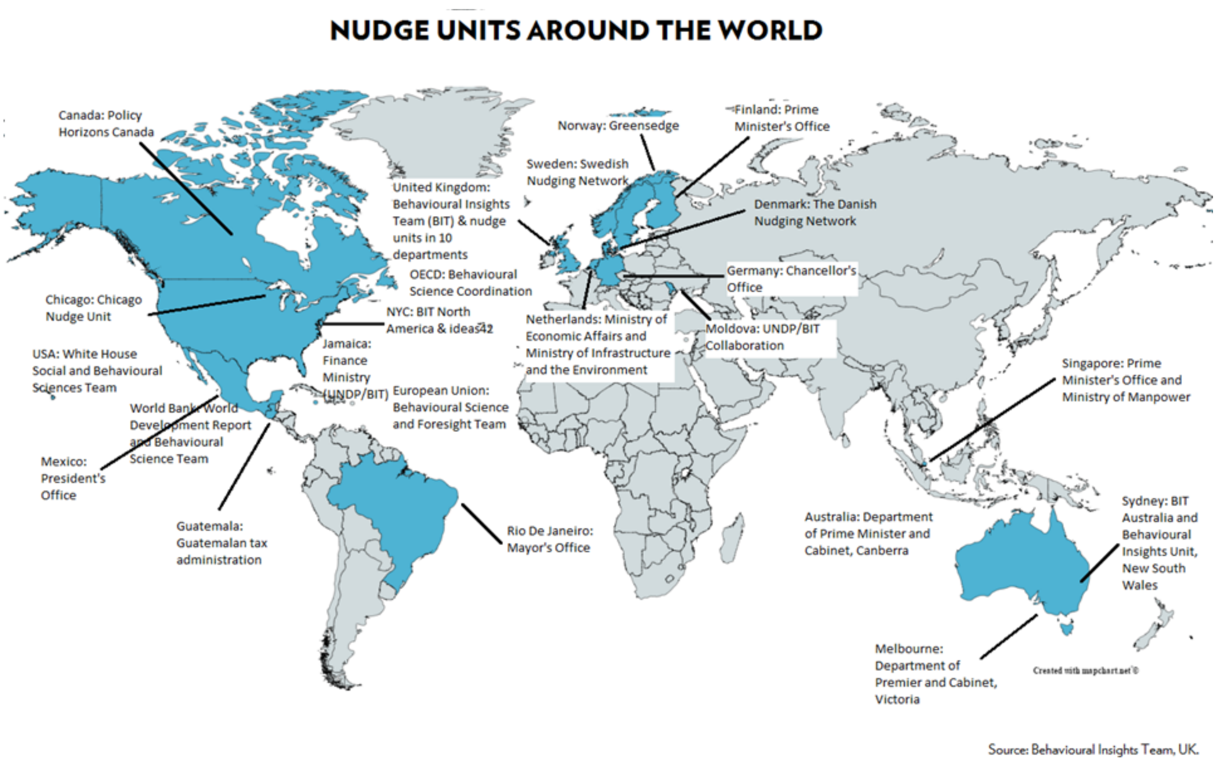

Figure 1.2: Nudge Units Around the World. Source: Behavioral Insights Team, UK, 2016

section, ridesharing is a highly competitive market with private companies entering different market segments. At the same time, governments are interested in ensuring a fluid and efficient transportation system and view ridesharing as an innovative solution to transportation. Individuals, in general, hold a positive view of ridesharing as well. The interests of business practitioners, policymakers, and customers are aligned in promoting the ridesharing practice. The lack of ridesharing adoption today urges us to test behavioral insights at both levels to understand the motivations and constraints.

1.2.2 Toward a Long-Term Behavioral Change

As explained in the previous section, behavioral interventions can be applied both at the business and policy/external shock level. Businesses may focus on immediate, short-term interventions that target cognitive biases, with a higher level of precision and personalization. Policies tend to change the environment that individuals interact with, and so tend to be more generic and less personalized. We argue that both levels work together for the long-term adoption and habit formation of a ridesharing practice. Here, we use the definition of habit as Hodgson (1998): "(A habit is) a largely non-deliberative and self-actuating propensity to engage in a previously

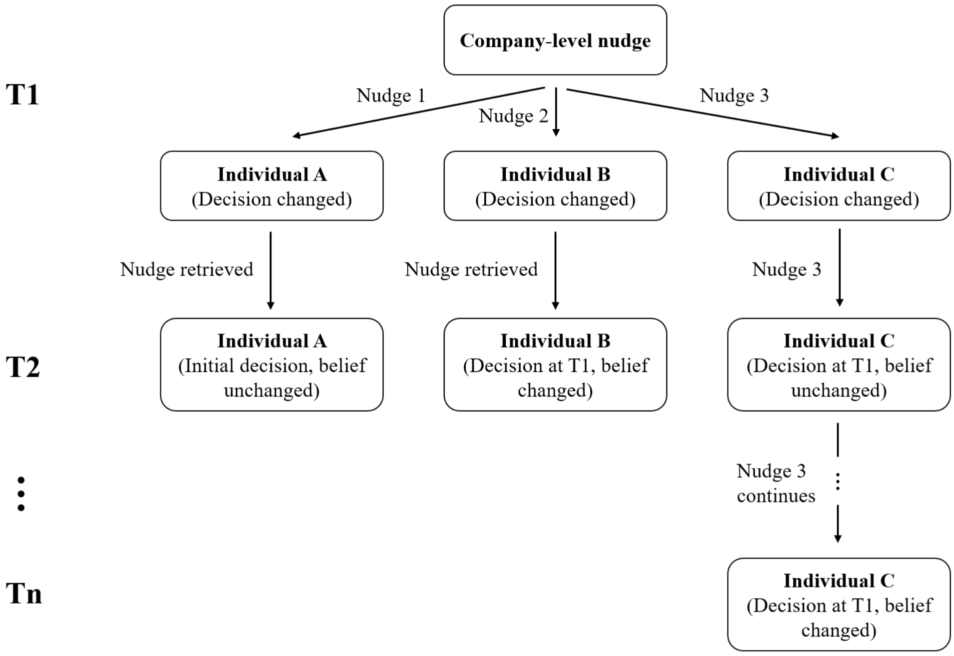

Figure 1.3: Business-Level Nudge and Behavioral Change. Author's Own Contribution

adopted pattern of behavior ... a form of self-sustaining, non-reflective behavior that arises in repetitive situations." Labrecque, Wood, Neal, and Harrington (2017) argue that existing habits may impede the adoption of a new product and that it would be easier to encourage its adoption by integrating the new product into the existing habits. We show how business and policy level behavioral interventions could achieve this in different ways.

Figure 1.3 illustrates how business-level behavioral interventions work. At time 0, individuals A, B, and C have their prior beliefs and decisions. We assume that none of them rideshare, and they believe that they are making the correct decision. At time 1, the company launches a personalized nudge campaign towards the three individuals. Individual A sees an advertisement entitled "You have 50 € in your ridesharing account. Try it or lose it!". Since she is very loss averse (Tversky & Kahneman, 1991), she decides to rideshare to work as a passenger at time 1. Individual B is told that she could earn an important sum of money if she offers seats in her car on her way to work. Lured by the money, she also starts using the service at time 1. Individual C receives an invitation to participate in a competition between her company and the employees of the other companies in the same industrial zone, in which the company with the longest ridesharing distance on the way to work wins. Some of her colleagues have already registered, so she also starts using the service as a driver at time 1.

At time 2, the free trial ends for individual A, and now she needs to pay. She really enjoyed the free rideshares, but she has not completely decided whether to continue to rideshare to work. She still believes that the buses and subways are more reliable than ridesharing. Now that she needs to pay, she switches back to her initial travel mode. The company also decides to stop subsidizing drivers as it did at time 1. However, individual B now enjoys having some company during her way to work, so she decides to keep using the service even in the absence of a monetary incentive. For individual B, her belief of the advantages of ridesharing has changed, and a new habit is created, even though the nudge does not last too long. Another person facing the same situation may decide to switch back to solo driving once the monetary incentive is withdrawn. We discuss when the monetary incentive works and when it does not work in the next section.

For individual C, the competition nudge lasts for several time periods. Since it solves the parking shortage and is highly rated by employees, the industrial zone decides to integrate it into their transportation solution. Individual C keeps ridesharing to work because besides saving money, ridesharing also brings joy and sense of achievement. The non-monetary incentives are as important as the monetary ones. Eventually, ridesharing becomes a culture among colleagues. For individual C, her beliefs and habits have also changed, and so have those of many of her colleagues.

This hypothetical example presents some typical scenarios in business-level nudging. Due to various constraints, nudges often cannot last long. Once the nudge is withdrawn, individuals may switch back to their initial behavior, as for individual A. They have not had enough time to form a new habit or to change the belief about the relative attractiveness of ridesharing. Some short-term nudges may induce long-term adoption of ridesharing, as for individual B. E. Frey and Rogers (2014)'s paper identifies four pathways that make behavioral interventions persist. One of these pathways is "changing how or what people think". For individual B, ridesharing is now more attractive than the initial commuting mode, but such a change of mind could not have happened had she not tried. The long-term nudge, like the group competition case of individual C, is more likely to lead to habit formation. Group competition also fits another pathway identified by E. Frey and Rogers (2014) as "external reinforcement" by peers, which

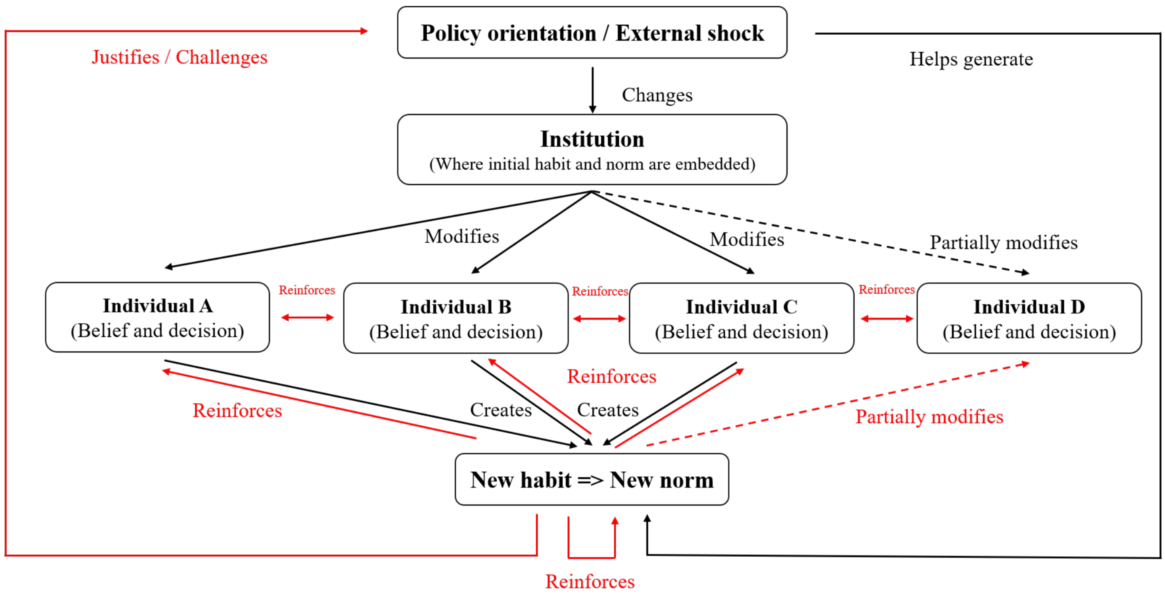

Figure 1.4: Policy-level nudge/External shock and Long-Term Behavioral Change. Author's Own Contribution

naturally lasts for a longer period even after the nudge is withdrawn.

External reinforcement could also come from the institutional level. When a new behavioral policy is implemented, or similar external shock takes place, it may have a more prolonged, even permanent impact, as illustrated in Figure 1.4. Policy orientations or shocks aim to change the current institution in which an individual's initial habit is embedded. Here, we refer both to the formal institutions like laws, and to the informal institutions like conventions and norms, as defined by North (1991). Those norms then shape individual beliefs and preferences (Alesina & Giuliano, 2015), which eventually form the habits that are in line with the norms.

Take the hypothetical example of a policy that shuts down trains connecting small cities in France. Before the trains are shut down, the habit for individual A is to take trains for long-distance travel. As she is used to trains, when she compares taking a train and ridesharing, she believes that taking a train is a better option, because it is faster and does not need organizing with others. She may also believe in the advantages of ridesharing: cheaper, especially for the last-minute booking; less detours for some itineraries; more flexible time schedules; and so forth. Hence she has no incentive to change her beliefs or decisions.[22] for her habitual mode.

The shut down of trains forces individual A to search for non-habitual ways to commute.

[22]She may also be unaware of ridesharing, because she does not need to know extra information other than that

She could either rearrange her schedule to travel on another day (which is not available if the train line is completely shut down), or to drive herself (which is not available if she does not have a drivers license), or to rely on alternative transportation modes like coaches or ridesharing. Even if her preference for trains remains high, she may gradually start to try ridesharing either as a driver or as a passenger. She is not the only case. The change may also happen to similar individuals B and C. As more and more people adopt the new practice, a new convention will emerge. Now, individual A may feel more comfortable and more used to rideshare. She adapts her beliefs accordingly. Now, the advantages of ridesharing become more salient to her. Besides, all her peers rideshare and society encourages it. With time, ridesharing becomes a new habit.

Of course, the change is not as straightforward. Several factors contribute to the process of the long-term habit change, as shown in Figure 1.4. Firstly, policy nudges/orientations and shocks may work directly on the norm. At the same time as shutting down train lines, the state and local governments, as well as ridesharing companies, may launch campaigns that promote ridesharing as a more economical and more environmentally-friendly lifestyle using various nudge techniques; and the train company itself may also suggest its users switch to alternative modes like ridesharing. The second factor is the peer effect. Since the majority of the group adheres to the norm, they will reinforce the norm amongst themselves. The peer effect also helps others to adhere: the more people who adopt ridesharing, the easier it is to attract the hesitant individuals to join (Granovetter, 1978). Take the example of individual D. The new policy may not directly change her beliefs and decisions about transportation modes. She is so adverse to ridesharing that she is willing to endure all the costs of using the other transportation modes. However, when all her peers start ridesharing and keep telling her their positive experiences, she may eventually switch to ridesharing to be like the others. Thirdly, the creation of a new norm and a new habit may, in turn, justify the choice of the policy. The policy then extends in scale and duration, which in turn reinforces the existing norm.[23]

[23]In the opposite case, the creation of an unwanted norm may challenge the policy choice and lead to its suspension.

1.2.3 French Ridesharing Policy Advances

We argue in the previous section that policy nudges/orientations are necessary for a long-term behavioral change. Fortunately, the current French policy is quite in favor for the development of ridesharing solutions, as well as other innovative mobility solutions. Under the encouraging policy environment, many local governments have taken ridesharing initiatives in recent years. As mentioned previously, some regions are building their own ridesharing platforms, and some cities are experimenting with the integration of ridesharing into the public transportation system.[24] Local governments are also buyers of ridesharing solutions, especially those based on meeting points dedicated to solving local transportation problems. Financial subsidies are also commonly used to support the sector in its infancy before the large scale behavioral change arrives.[25]

In October 2017, the Île-de-France mobility authority launched a three-month initiative to subsidize by two euros for each shared ride undertaken within ten participating companies covering urban and rural areas of the capital region. The initiative was extended until October 2018 after its initial success. Starting from May 2019, all annual subscribers of the region's public transportation pass (Navigo) will benefit up to two free ridesharing trips per day, while drivers' gains are subsidized, following the trend of integrating ridesharing into the public transportation system. As the practice of ridesharing spreads, and the need for subsidies continue, in 2018, the French government implemented a national ridesharing registry.[26] The registry allows all ridesharing service providers to send data that can demonstrate that a shared ride has taken place once it is officially verified. This assures mobility authorities can subsidize service providers and participants without the fear of fraud. The registry also serves as a data repository that helps track the evolution of ridesharing practices.

On November 18th, 2019, the French mobility law (*Loi d'Orientation des Mobilités*) was approved. The law addresses the challenges in mobility faced by France today, and ridesharing,

[24]For example, the Troyes Champagne metropolitan began collaborating with Karos in September 2019. Passengers can use public transportation tickets to rideshare before or after taking public transit. The local government subsidizes each shared ride so that drivers receives at least two euros per passenger.

[25]Fundraising, operating revenues, government subsidies and prizes/awards are the four primary income sources for most ridesharing businesses.

[26]More information about the registry is at http://covoiturage.beta.gouv.fr/

together with other innovative transportation modes, are encouraged as alternative solutions to the social and environmental challenges.

For local governments, the law gives them more flexibility to support ridesharing. They can keep subsidizing daily ridesharing, both for drivers and for passengers, as they have been experimenting with since October 2017. They can also assign dedicated roads to ridesharing (like HOVs lanes in the US) close to metropolitan areas following some promising experimental programs.[27] In terms of experiments with innovative mobility solutions, rural areas are also given more flexibility as the law allows the government to issue exemptions for experiments that may not be included in the current legislation.

Work commutes are also a vital component to convert to ridesharing. The law assures this by obliging employers to make an effort. For companies with more than 50 employees, the transportation mode of employee work commutes must be taken into consideration and be facilitated. Besides the existing programs like subsidizing public transportation subscription fees, employers are also encouraged to allow more flexible working schedules and locations, as well as to incentivize employees to cycle and rideshare.[28] Employees could receive up to 400 euros per year from their employers for their expenses of their work commutes by cycling or by shared mobility modes, including ridesharing. Before the approval of the law, the cap was 200 euros per year and only applied for expenses for on cycling to work.

The new law also aims at a more environmentally friendly future of mobility, in which ridesharing is favored. To ease the behavioral change of individuals to switch from the culture of owning a car and driving alone, all advertisements of motor vehicles must also contain information to encourage people to use shared mobility modes. This enforcement is similar to the messages printed on cigarette packages to inform consumers of the risks of smoking.

Under the new mobility law, ridesharing service providers, mobility authorities (whose structure have been simplified in this law), local governments, and businesses now have clearer guidance for developing ridesharing. For residents, their behavior will gradually change as

[27]There have been experiments on the A6-A7 highway near Lyon, and the results are encouraging. The A48 highway will also partially be reserved for ridesharing starting from 2020.

[28]Since January 1st of 2018, companies of more than 100 employees are already obliged to make a mobility plan (*"plan de mobilité"*) to incentivize their employees to use public transportation and to rideshare. The current law makes the requirements stricter.

under the incentives given at business levels and the growing culture of sharing rides.

The thesis contributes to the understanding of both business-level incentives and policy orientations. The first two papers report two field experiments on non-monetary motivations of drivers of a rural ridesharing provider, Ecov. While it appears that the most obvious business-level nudge is to offer monetary incentives, we argue that non-monetary motivations could play an important role and that monetary incentives may reach a limit in effectiveness. In the third paper, we investigate the inter-city ridesharing supply and demand changes during the 2018 national railway strike. We also estimate the well-being impact of ridesharing during strike and more broadly, the well-being comparison of train commuting versus ridesharing. This investigation of a railway supply shock may be useful for policymakers who wish to implement similar policies induced by external shocks.

CHAPTER 2

MORE GENEROUS FOR SMALL FAVOUR? EXPLORING THE ROLE OF MONETARY AND PROSOCIAL INCENTIVES OF DAILY RIDE SHARING USING A FIELD EXPERIMENT IN RURAL ÎLE-DE-FRANCE

Dianzhuo Zhu[1]

Abstract

This paper conducts a field experiment with a spontaneous short-distance ridesharing company to understand the interaction of monetary and prosocial motivations of drivers. Drivers pick up passengers (hired by the author) without knowing the amount that they will be paid and can decide privately and freely after the trip whether to receive payment, to donate it to charity, or to do nothing. Both monetary and prosocial motivations are found to be relevant. However, prosocial incentive works better for short-distance (5 km) trips, while monetary incentive seems to be more efficient for long-distance (20 km) trips. Drivers tend to be more generous to give up their compensation when the favour they offer is small. The author discusses the importance of taking prosocial motivations into the design of daily ridesharing, especially when the sector focuses on the monetary incentive of the date.

Keywords: Ridesharing, Monetary, Prosocial, Field Experiment

[1]M&O-DRM Lab, University Paris-Dauphine, PSL Research University. This chapter is based on the published paper of the author (D. Zhu, 2017). I thank managers and colleagues Ecov for the support of the design and conduct of the experiment. I also thank *PNR (Parc Naturel Régional) du Vexin* for funding the research. I keep the text of the paper in the main part of the chapter, with formatting modifications and correction of some grammatical errors and expressions to be in line with the thesis. For example, I replace “pro-social" by “prosocial”, “ride-sharing” and “ride sharing” by “ridesharing”, “annex” by “appendix”, etc. The citation style, the captions and the table alignment of the published version have also been modified to be compatible with the thesis. I add additional materials that are not included in the published version due to space limit in the appendices of the chapter. The published version applies a less technical and more pedagogical tone because the journal is often consulted by the practitioners. The original version of the paper can be found on http://chairgovreg.fondation-dauphine.fr/sites/chairgovreg.fondation-dauphine.fr/files/attachments/DWEJ%20108_Zhu.pdf.

Recent years have witnessed the rise of sharing economy both in industry and in academia (Botsman & Rogers, 2010). Although this term still lacks a universal definition, a large part of the sharing economy movement is based on two-sided platforms (Roth & Sotomayor, 1992). They match “sharers" with “sharees", so that “sharers" offer temporary access of their personal good to “sharees", either for free or not. The most famous companies – Airbnb and Uber – are both of this kind. Since platforms do not own any shared goods themselves but need to favour the sharing of private, often very personal goods with strangers, who have not done it before, understanding their motivations becomes an urge for platforms and policymakers.

Several studies have been made using various platforms. Methods like surveys and interviews helped to seek out existing motivations. Shaheen et al. (2017)’s survey on Blablacar’s drivers and passengers found that for passengers and drivers, both practical, extrinsic motivations (save money and time) and ideological, more intrinsic motivations (pleasant to socialize with others, willing to help people and to save the environment) gain a high level of agreement, although money-saving outperforms all other motivations. Gerber and Hui (2013) showed that creators of crowdfunding projects often have more extrinsic purposes like raising funds and expanding awareness, while project supporters are, in general, more intrinsic, who mostly want to support a good cause and to be part of the community. Natural field experiments (in real settings, without the participants knowing that they are in an experiment, see the definition of Harrison and List (2004)) have entered the domain of the sharing economy research recently and helped to measure the quantitative effect of incentives. An example would be R. Chen, Chen, Liu, and Mei (2017)’s paper on team competition and the crowdfunding amount.

However, not enough attention has been paid to the relationship and interaction of monetary and non-monetary incentives, despite its relevance in the sharing economy. The word “sharing economy" combines two seemingly contradictory terms: “share", which often represents the altruistic, non-profit side of humanity, and “economy", which leads immediately to the picture of a world that chases efficiency, analyses monetary costs and benefits, and lets heartless market rules decide everything. Although sharing one’s home with strangers via platforms is new, sharing it with friends and family members or even friends’ friends is amongst the oldest practices of human society, and continues to exist today–we would not ask our friends to go through Airbnb if they ask for a short stay! In fact, there have always been tough debates towards whether a platform should be considered as “true" sharing economy, and among some idealists, a simple improvement of resource usage efficiency without the sense of community should not be included in the sharing economy.[2]

Ideological debates set aside, today’s version of the sharing economy does witness the combination of the “sharing" side and the “economy" side. Market efficiency helps scale up sharing around the world. Platforms position themselves in a way that is either more sharing-oriented or more economy-oriented. Coexisting with, and even earlier than Airbnb, Couchsurfing allows people to stay at local hosts’ places for free, under the idea of solidarity and general reciprocity (Lauterbach, Truong, Shah, & Adamic, 2009). Together with various ridesharing services, hitchhiking continues to work. All these require us to explore more possibilities on the organizing forms of the sharing economy, on when and why people share for free or for a price. Is there only one motivation that dominates the decision making, and if not, how do different contradictory motivations interact?

2.1 Why Focus on Short-Distance Daily Ridesharing in Rural Areas?

Ridesharing is one of the important pillars in the sharing economy.[3] Ordinary drivers are mostly seen using platforms for long-distance, city-to-city trips (Blablacar). Uber, the most successful private platform for satisfying short-distance commute demands, relies on professional drivers who wander around the city. The only difference compared to taxi drivers is that they are with their own cars. The price is also too high for daily commutes. Ordinary drivers are still reluctant to enter the short-distance, daily ridesharing market. The blame is not entirely on them – who likes the burden of opening a mobile app, entering their trip,[4] waiting for a passenger to validate, negotiating the picking-up location and making a detour for only 2-3 euros?[5] Nev-

[2]For an example of criticism, see Pick and Dreher (2015)’s article on Ouishare magazine. http://magazine.ouishare.net/2015/05/sustaining-hierarchy-uber-isnt-sharing/

[3]Here, we distinguish ridesharing (driver and passenger are both in driver’s car and go to the same destination) from car sharing (a person rents a car from a car rental company or an individual, without the latter driving with this person).

[4]Some start-ups are trying to skip this step by using machine learning to predict drivers’ trips.

[5]The early version of organized car sharing—carpooling in the 1960’s US—saved these steps because picking up points are at the entrance of highway, see Chan and Shaheen (2012) for a historical review. This form is still performing well now in San Francisco (Shaheen et al., 2016).

ertheless, these unprofessional drivers could play a crucial role in offering more efficient trip solutions, solving congestion problems, and releasing the burden of investing in road infrastructures. Policymakers are putting great attention on unblocking this market.[6] The benefit will be even larger for rural areas since the public transportation system there cannot satisfy all needs. People without cars still find themselves in difficulty to go anywhere.

2.2 Which Field and What Behavioral Theories May Apply?

The key to onboarding ordinary drivers relies either on decreasing the cost per trip or on motivating them through non-monetary channels, which is to say, to balance the term “sharing" and “economy".

We collaborate with a ridesharing company, which operates in rural villages of Île-de-France (Great Paris Area). It is a spontaneous ridesharing system (more description in the experiment design part) which minimizes drivers' effort of picking up passengers and allows drivers to decide whether to earn money or not. Pilot analysis on declarative questionnaire archive data shows that the majority of drivers mention solidarity as their first motive. Historical data before the experiment (January 2017) also shows that the overall ticket cash-out rate is low.

However, behavioral theories suggest more complex reasoning. Andreoni (1990)'s paper argues that people may behave prosocially (in this case, refuse the payment) because they want to feel like a good person (warm-glow giving). Another famous theory called crowding-out shows that monetary incentives may backfire intrinsic motivations (B. S. Frey & Jegen, 2001). In this case, drivers do not want money since it will ruin the pure pleasure of helping others. Despite the fact that drivers may hold esteem-related or altruistic motivations, a simple cost-benefit analysis may also explain low cash-out rate: most of the existing trips are for very short distances. Drivers may have simply forgotten the ticket or find it too costly to cash several cents out, especially when the cashing out action is not automatic. Deci, Koestner, and Ryan (1999) and Cameron, Banko, and Pierce (2001)'s meta-analysis also prove that the crowding-out effect is framing-dependent. If extrinsic rewards are on the performance level but not on the result,

[6] See report on Assises de la mobilité, the planning of new law on transportation. The transportation ministry has postponed several ongoing infrastructural projects in favour of a new mobility strategy, especially light modes like electronic bicycles, ridesharing, and autonomous buses. Source in French. http://www.lefigaro.fr/flash-eco/2017/09/19/97002-20170919FILWWW00011-lancement-des-assises-de-la-mobilite.php

if actors endorse the socially beneficial side of the incentive, if actors give positive feedback to recipients, or if the extrinsic incentives are chosen by the recipients themselves, a crowding-out effect may not happen.

2.3 Hypothesis

So, are drivers really not interested in monetary payoffs? If they are not, for which reasons? If they are, for how much money? How will drivers' choices be affected by framing? We made some preliminary hypotheses and tried to answer some of the questions by an exploratory field experiment.

Hypothesis 1: Some drivers do choose not to cash out for prosocial reasons, like warm-glow or to avoid intrinsic motivation crowding-out.

Hypothesis 2: However, this effect will be partially compensated when the monetary incentive is sufficiently large.

The tricky part is to disentangle cash out behavior from a pure cost-benefit point of view and cash out behavior when prosocial reasons are taken into account. If only operational costs are considered, as long as the price surpasses the drivers' cost of cashing out money, drivers will cash out. Since each driver's perceived cost is unknown and not unified, the higher the price level, the more likely that the driver will cash out. Under the prosocial reasoning schema, the positive relationship of the price level and cash-out rate still holds. How can we be sure that some drivers do refuse to cash out because of prosocial reasons, no matter who they are and what these reasons are?

Charitable giving offers an option. In the classic version of laboratory experiments like the dictator game, “dictators" are given an endowment and can freely decide to divide this endowment (usually money) between themselves and a passive recipient. The omnipresent positive amount of transfer is often considered as a proof of prosociality (Henrich et al., 2004). Eckel and Grossman (1996) used charity as recipient and again found a positive amount of transfer, even higher than when the recipient is an anonymous person. In the setting of the ridesharing model, if under the same price, more drivers are willing to treat the ticket when donation option is offered, we can say that these drivers are purely motivated by prosocial reasons. Although we cannot say that those who neither donate nor cash out are not prosocial, it would be enough to prove prosociality.

2.4 Experiment Design

2.4.1 How Does the Service Work?

The company's ridesharing system does not require downloading a mobile application. Instead, they build ridesharing stations in villages. Passengers go to the station, buy a ridesharing ticket to a destination using the machine at the station, take the printed ticket and wait there. At the moment when the ridesharing request is passed, the destination will be shown on a screen several hundred meters in front of the station. All drivers passing by can see the request, and those who are going to the same destination and are willing to help can slow down and pick the passenger up. At the end of the trip, the passenger can give the ticket to the driver. The amount that the driver can get is printed on the ticket. Drivers need to go to the service's website to cash it out. They may either be happy to earn some extra money or just to help without compensation. Demonstrations of the station and the screen could be found in Appendices A.1 and A.2.

2.4.2 Who?

We hired people to act as passengers to make requests at a station and to wait for drivers to pick them up. Before the experiment, hired passengers are given a briefing and a practical guide that detailed what they should and should not do. To summarize, they have to choose the destination that we ask them to choose (more information below). They are also required to chat with drivers in a natural way during the trip to learn basic information about drivers (for example, driver's gender, approximate age, knowledge of the service, history of participation, etc.). They report this information in a questionnaire after each trip. At the end of the trip, they need to give the ticket to the driver and explain clearly that drivers can cash out the amount on the ticket if they go to the website or donate it to a charity (when donation option if offered). They also need to mention the amount, so that every driver is clear about what they can get, in case that some of them forgot to look at the ticket even though they would have been interested in the amount had they known. They also need to make clear that in no case will the money be given back to them. However, hired passengers can never try to influence drivers' choices by highlighting that one choice is "better" than the other. Their role is to give necessary information neutrally and let the drivers decide. This point was made clear during the briefing stage. Appendices A.3 and A.4 provide training materials and questionnaires for passengers.

Drivers can be whoever passes by and decides to pick the passenger up, as in the real settings. Passengers will at no time tell drivers that they are in an experiment, in order to observe the most natural behavior of drivers during and after the trip. Since we cannot control the identity of the driver before each trip, passengers could encounter any type of driver when they wait. If we equalize the overall time period of test for each control and treatment group, we could say that drivers who eventually stopped for each group are of the same profile distribution, since randomization is given by nature. Michelitch (2015)'s work also uses the randomness of taxi drivers passing by to conduct bargaining experiments. Prices are not shown on the screen so that there is no risk of driver self-selection bias under a different price level by the time they see the request.[7]

2.4.3 When and Where?

The main departure place of the experiment is village A, which has a ridesharing station by a main road with heavy traffic. Another advantage of the station is that the screen is located at an upward slope, which is 200 meters in front of the station. Passengers are not visible at the moment when drivers climb upward and see the screen. Once they have climbed up, then need to slow down immediately in order to turn a bit to the right and stop at the parking lot next to the passenger. This ensures that drivers barely have time to carefully check passengers' appearance and discriminate so that the self-selection issue of participation is well controlled.[8]

From this village, short (about 5 km) and long (15-20 km) distance trips are tested.[9] The destination for short-distance trips is a nearby village B, also close to the main road. The

[7]Of course, drivers who have participated would know that they are getting paid, some even know for how much. This question was included in the knowledge of the service part of the questionnaire. Data shows that most drivers do not know the amount that they are getting paid, even though some know that it is not for free. In any case, all drivers will be given the same information after the trip to de-bias.

[8]Weather also helped in reducing biases. The experiment was conducted in winter, when all passengers were wearing heavy clothes, scarfs and sometimes hats, making it difficult to judge their appearance from far away.

[9]In the experiment setting, we use "short" and "long" to distinguish the relative distance. Under the frame of ridesharing in general, they are both short distances—inside or between villages and for frequent commute needs.

destination for long-distance trips is either a shopping center in village C next to an exit of the main road or village D, 2 minutes ahead of village C if you drive along the main road. All four villages are in the same agglomeration, and since they can all be reached by the main road and that villages C and D are larger, a typical resident of village A goes to all the other villages for shopping, administrative tasks, leisure or work. A typical resident from other villages who passes by the main road in village A also goes to the direction of village D and will pass by the other villages. We ensure that under each distance, drivers are of the same pool with comparable socio-demographic profiles.[10]

2.4.4 How?

The experiment lasted for five weeks, from the 9th of January to the 12th of February in 2017. In each week, different treatments were applied, as shown in Table 2.1 below.

Table 2.1: Experiment Design: Treatment and Control Groups

Week	Experiment Design	Short Distance Price (5 km, in €)	Long Distance Price (20 km, in €)
Week 1 (control)	Normal price, no donation	0.45	1.8
Week 2	Tripled price, no donation	1.35	5.4
Week 3	Normal price, with donation	0.45	1.8
Week 4	Tripled price, with donation	1.35	5.4
Week 5 (post-experiment control)	Normal price, no donation	0.45	1.8

We are not able to totally randomize each treatment and control because of technical complexity.[11] We thus decided to test each treatment for a week. Since prices are not shown on the screen, drivers will not see the treatment unless they participate. For new participants, price levels for past weeks have no effect on their judgment of the price they receive. Drivers who already participated during the test behave differently. We discuss these drivers in the next section.

The first week is for control, in which we standardize the basic price level, holding the

[10]For the convenience of hired passengers and the efficiency of time and budget, some return trips are made from village B and C, where there are also ridesharing stations. However, they count only for a minority of all tests done, and the driver pool remains the same. It is easier for drivers to see the passenger before deciding to stop in these stations, though. The data analysis part will show more evidence.

[11]The donation option can only be activated and deactivated at the station and has to enter the maintenance password for manipulation. We cannot give it to hired passengers, neither is it practical for them to manipulate at each trip.

per-kilometer price the same for short-distance trips (0.45 euros for 5 km) and long-distance trips (1.8 euros for 20 km). No donation option is mentioned on the ticket given to drivers. In the second week, we set the high price level for each distance with tripled price, which is the maximum legal level that we can offer under a ridesharing regime. In the third and fourth week, we repeat the price levels of the first and second weeks but with a donation option on the ticket. Passengers will also mention this information before getting out of the car. In the last week, we repeat the control level in order to see if the simple exposure of intensive requests changes drivers' cash out behavior. Examples of tickets with and without donation options are available in Appendix A.5. The web page that drivers need to choose between cash out and donation is presented in Appendix A.6.

2.5 Data Analysis

2.5.1 Descriptive Data

At the end of the fifth week, we have collected 197 effective trips, with around 20 observations each week for each distance. Effective means that those trips are succeeded, tickets are given, key messages are explained to drivers, and drivers are not suspicious about the experiment. Figure 2.1 shows the trip number in each week and how drivers treat tickets. In this figure, “new drivers" contains those who have never participated during the experiment period before the current trip, and “all drivers" include those who have already participated before. Since we would not know who the driver will be ex-ante, the same driver may end up picking passengers up several times. These drivers may behave differently since they have already known some information and that they may face different price levels in different weeks.[12] We report statistics both with and without experienced drivers in the following sections. We discuss these data in the next section.

Around 95% of short-distance trips (96 out of 102) depart from village A. For long-distance trips, 38% of the trips (36 out of 95) start from village B, or C. Passengers are from different origins and have participated in different treatments, as shown in Table 2.2.

[12]However, none of them was suspicious about being in an experiment. Some of them reasoned the change of price as a strategy made by the company to reward drivers in non-peak hours. Others thought that passengers decided to pay a higher price.

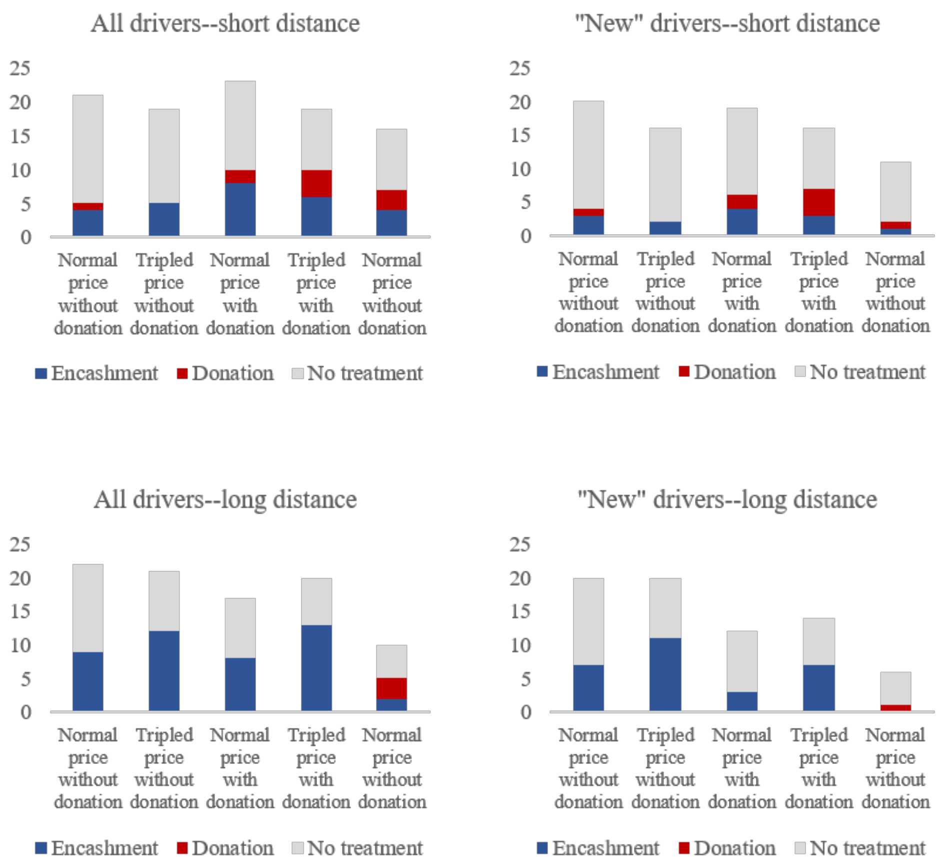

Figure 2.1: Drivers' Ticket Treatment Behavior Each Week

Table 2.2: Passenger Profile and Trip Distribution

Passenger Ethnicity	Passenger Number			Share
	Male	Female	Total	
European	5	5	10	58.82%
Asian	1	2	3	17.65%
African	2	2	4	23.53%
Total	8	9	17	100%

Passenger Ethnicity	Total Rideshared Trips			Share
	Male	Female	Total	
European	31	51	82	41.62%
Asian	13	55	68	34.52%
African	10	37	47	23.86%
Total	55	144	197	100%

2.5.2 Biasness Checks

Highlights (Tables 3-6): The purpose of this part is to check if some of the key variables that are not included in experimental tests influence ticket treatment behavior significantly differently in different control and treatment groups, which creates bias. No significance was found on how passenger gender, passenger age, or driver gender may influence driver behavior. Older drivers cash out less often, but different aged drivers are distributed similarly under each price level. Executing different treatments in continuous weeks instead of randomizing all treatments together does not bias drivers' cash out behavior either.

Tests show that passengers' socio-demographic profiles have no significant effect on drivers' ticket treatment behavior. Table 2.3 shows that at least for new drivers, for each treatment, drivers who pick up different passenger genders behave similarly in cash-out rate and donation rate, the same for drivers who pick up different passenger origins (None of the statistical tests is significant).

Table 2.3: Drivers' Behavior Difference Under Different Passenger Profiles

		Passenger gender (Fischer exact test)		Passenger origin (Anova test)	
		Cash-out rate	Donation rate	Cash-out rate	Donation rate
Short distance	All drivers	0.041^{**}	0.251	0.096^{*}	0.738
	"New" drivers	0.237	0.317	0.586	0.904
Long distance	All drivers	0.129	-	0.21	-
	"New" drivers	0.334	-	0.218	-
Normal price	All drivers	0.547	0.528	0.032^{**}	0.147
	"New" drivers	0.503	0.522	0.047^{**}	0.124
Tripled price	All drivers	0.108	0.736	0.971	0.134
	"New" drivers	0.215	0.653	0.359	0.194
Without donation	All drivers	0.236	-	0.013^{**}	-
	"New" drivers	0.176	-	0.011^{**}	-
With donation	All drivers	0.458	0.508	0.776	0.841
	"New" drivers	0.403	0.42	0.155	0.993
All tickets	All drivers	0.229	0.553	0.098^{*}	0.933
	"New" drivers	0.342	0.527	0.288	0.97

* $p < .1$, ** $p < .05$, *** $p < .01$

Drivers' profiles are more difficult to obtain because drivers are not obliged to register in order to participate. We use passengers' observational data for gender and age group as basic information and correct estimation error using registration data of drivers who cashed out or donated money. Passengers estimate drivers' ages in 4 groups: 18-30, 30-45, 45-60, and above 60 years old. Table 2.4 shows that in general, driver gender does not influence their ticket treatment behavior significantly. The only exception is for week 2, where female drivers cash out significantly more often than male drivers, especially for new drivers. However, we can still say that driver gender does not bias the results systematically.

Table 2.4: Drivers' Behavior Difference Under Different Driver Profiles

		Driver gender (Fischer exact test)		Driver age group (Anova test)	
		Cash-out rate	Donation rate	Cash-out rate	Donation rate
Short distance	All drivers	0.477	0.407	0.514	0.136
	"New" drivers	0.094*	0.475	0.507	0.084*
Long distance	All drivers	0.224	-	0.002***	-
	"New" drivers	0.435	-	0.003***	-
Normal price	All drivers	0.192	0.573	0.993	0.141
	"New" drivers	0.289	0.595	0.601	0.129
Tripled price	All drivers	0.416	0.194	0.008***	0.244
	"New" drivers	0.234	0.221	0.002***	0.235
Without donation	All drivers	0.161	-	0.414	-
	"New" drivers	0.079*	-	0.166	-
With donation	All drivers	0.545	0.468	0.04**	0.081*
	"New" drivers	0.533	0.437	0.013**	0.084*
All tickets	All drivers	0.206	0.435	0.043**	0.075*
	"New" drivers	0.173	0.433	0.007***	0.066*

* $p < .1$, ** $p < .05$, *** $p < .01$. Post-experiment control is not included in the table.

Age plays a more important role in defining driver behavior. The right block of Table 2.4 demonstrates that under the tripled price (week 2 and 4), especially for long distances, drivers under 30 years old cash out significantly more often than other age groups.[13] When the donation option is offered, older drivers are more likely to donate. This makes sense intuitively—young drivers are more sensitive to payment and are more willing to use the Internet. Older drivers, however, may refuse to cash out because of small amount or of reluctance to technology but are more prosocial in general since they are more willing to donate money to charity.

This raises the question of whether drivers of different age groups distribute equally. From Table 2.5, we can see that middle-aged and old drivers (more than 45 years old) are less representative in long-distance trips if we take all drivers into consideration, which may explain the higher cash-out rate for long-distance trips. However, when we only consider new drivers, age groups are distributed equally both for short-distance and long-distance trips. To summarize, driver gender and age do not bias our results for new drivers.

[13]The table itself only shows that different age groups cash out under significantly different frequencies. If we look at each age group, we can see that drivers under 30 years old cash out more often. Raw cash-out rate is not presented here due to limited place, but available upon request. The same for donation rate data.

Table 2.5: Driver Age Group Distribution Difference

		P-value (Anova test)
Short distance	All drivers	0.064*
	"New" drivers	0.226
Long distance	All drivers	0.194
	"New" drivers	0.178

* $p < .1$, ** $p < .05$, *** $p < .01$

The concern of exposure effect is released as well. The last part of Table 2.6 shows that drivers who participated in the post-experiment control week do not behave significantly different compared to those who participated in the first week. Each driver's ticket treatment decision is more of a personal thing, independent of the number of requests having been made, although drivers will be more likely to stop if they see requests more often.

Table 2.6: Ticket Treatment Behavior Under Different Price Levels and Donation Options

		Short distance		Long distance		All tickets	
		All drivers	"New" drivers	All drivers	"New" drivers	All drivers	"New" drivers
Normal (above) vs. tripled (below)	Cash-out rate	0.566	0.522	0.19	0.107	0.188	0.158
price, no donation	Cash-out rate	0.861	0.677	0.243	0.121	0.271	0.213
Normal (above) vs. tripled (below)	Cash-out rate	0.545	0.602	0.222	0.184	0.29	0.258
price, With donation	Cash-out rate	0.826	0.865	0.272	0.191	0.435	0.349
	Donation rate	0.243	0.248	-	-	0.325	0.32
	Donation rate	0.255	0.258	-	-	0.378	0.367
Normal (above) vs. tripled (below)	Cash-out rate	0.587	0.474	0.08*	0.039**	0.115	0.087*
price, general	Cash-out rate	0.982	0.701	0.104	0.046**	0.175	0.123
	Donation rate	0.234	0.218	-	-	0.292	0.288
	Donation rate	0.25	0.227	-	-	0.335	0.329
Donation (above) vs. no donation	Cash-out rate	0.307	0.534	0.547	0.463	0.356	0.516
(below), normal price	Cash-out rate	0.412	0.764	0.845	0.616	0.557	0.809
	Donation rate	0.224	0.199	-	-	0.195	0.168
	Donation rate	0.132	0.111	-	-	0.11	0.088*
Donation (above) vs. no donation	Cash-out rate	0.5	0.5	0.423	0.524	0.371	0.51
(below), tripled price	Cash-out rate	0.721	0.626	0.606	0.774	0.579	0.814
	Donation rate	0.053*	0.051*	-	-	0.055*	0.038**
	Donation rate	0.034**	0.033**	-	-	0.038**	0.024**
Donation (above) vs. no donation	Cash-out rate	0.27	0.414	0.418	0.385	0.298	0.422
(below), general	Cash-out rate	0.395	0.602	0.688	0.583	0.494	0.699
	Donation rate	0.011**	0.009***	-	-	0.009***	0.005***
	Donation rate	0.009***	0.007***	-	-	0.007***	0.004***
Post-experiment (above) vs.	Cash-out rate	0.176	0.646	0.459	0.378	0.191	0.333
first week (below)	Cash-out rate	0.199	0.902	0.631	0.393	0.259	0.429

* $p < .1$, ** $p < .05$, *** $p < .01$

2.6 Hypothesis Check

Hypothesis 1: Partially verified. Yes, prosocial reasons for not cashing out money have been witnessed among drivers, but in our exploratory study, it can only be proven among short-distance drivers.

Table 2.6 compares if drivers of short-distance trips behave differently when different treatments are given (the same for long-distance). Each grouped horizontal block shows a comparison of two treatments, for example, normal or tripled price. Under each block, several ticket treatment behaviors are compared, either for cash-out rate or for donation rate (if available). As mentioned above, we measure both for new drivers' behavior differences and all drivers. Both Fisher exact test results (first line) and Chi-2 test results (second line) are reported for comparison.[14]

From the table, we can see that for short-distance drivers, tripling price from 0.45 euros to 1.35 euros has no significant effect on changing ticket treatment behavior (the first three horizontal blocks have no starred items). Drivers will cash out at about the same rate under tripled price as under the basic price level. This effect holds both when the donation option is not available and when the donation option is available for new drivers as well as for all drivers. Similarly, drivers will not donate more often when the price is tripled compared to the basic price level.

However, offering a donation option to short-distance drivers has significant effects on the donation rate (starred items for new drivers in the next three horizontal blocks). In general, when short-distance drivers can decide whether to donate or to keep the money themselves, significantly more drivers will donate. At the same time, neither significantly more, nor fewer drivers will cash the money out, which means that the donation option has attracted some drivers who do not want to cash out to eventually make an effort to go the website and donate.[15] The prosociality of some drivers is proved. It is also worth noticing that the significance applies both for new drivers and for all drivers.

[14]Both are common methods in comparing if two groups behave similarly in choosing yes-or-no questions.

[15]The donation option may also cause a change of mind of some drivers who want to cash the money out in the first place, but the effect is not significant here since the cash-out rate does not change.

For long-distance drivers, the results switched. Offering donation option has not attracted a single driver to donate, except for one driver in the post-experiment control (see Figure 2.1).[16] Meanwhile, the cash-out rate remains the same as well. It seems that drivers have thought through when making decisions. Those who decided to cash out will not change their mind facing the possibility to donate, and those who did not cash out will not donate either. They may be happy just to help a passenger, but they may also have forgotten the ticket or are not willing to give personal information to the company. More studies are required in order to disentangle prosocial motives of long-distance drivers.

Hypothesis 2: Partially verified. Monetary incentives may crowd in cash-out behavior of drivers who initially hold prosocial motives or find the cost of cashing out higher than the benefit, but this effect has only been proven on long-distance drivers.

We have seen from above that raising the price has no crowding effect on cash-out behavior for short-distance trips. However, when the price of long-distance trips is tripled, significantly more drivers will cash out tickets. Out of the added drivers, there may be some who hold prosocial motivations when the price is not tripled, which, again, cannot be disentangled from other motivations. In any case, we can prove that monetary incentive does have a crowd-in effect for long-distance drivers.

Learning effect: We also observe that for drivers who participated several times during the text, most of them end up cashing out money. According to the report of hired passengers, some drivers only reminded themselves of the ticket until their next trip. Some found that the long-term payoff may be interesting after several repetitions. Also, experienced drivers, compared to drivers who are unfamiliar with the service, are more likely to stop the next time they see passengers, even if they never cash out money.[17]

[16] There was no donation option printed on the ticket during the post-experiment control week, but some bugs led some drivers to the website with donation option.

[17] Although we are not 100% sure about drivers who never cash out. We are at least certain of one benevolent driver who has participated twice (confirmed by passengers) but has never cashed out nor donated.

2.7 Discussion and Further Research

The exploratory study shows that under the same per-kilometer price level, short-distance drivers react more actively to prosocial incentives. In contrast, long-distance drivers react more actively to monetary incentives. This effect holds even when we compare the tripled price of short-distance trips and the basic price of long-distance trips —- drivers are willing to donate for 1.35 euros but not for 1.80 euros, while the cash-out rates of these two do not differ significantly.[18] It is normal if drivers are willing to cash out more often when the price is higher, but for those who do not want to get paid, why won't they donate even when the price is high enough?

One hypothesis based on data analysis is that drivers justify their cash out behaviors differently. Under short-distance trips, drivers are more likely to think that they are offering help, and are thus less sensitive to price change but more sensitive to donation. Under long-distance trips, drivers spend more time with passengers and may start thinking that the time and fuel that "cost" them for taking a passenger on a trip that they would have driven in any case. They are still willing to help, but since the passenger gains more from them compared to a short trip, it is like they are offering a service, and it becomes more reasonable for passengers to share the cost. Even if they are not willing to cash the money out for various reasons, they are not willing to let a charity have "their money" either. Further research based on a more precise design is needed to test this explanation as well as to consolidate the relationship between distance and generosity.

The design of the exploratory study has its limits as well, which may bias the validity of findings. Drivers are given the same per kilometer payment, not the same absolute payment. To verify the hypothesis of generosity difference under different trip distances, we think the further step could be to give drivers the same absolute payment level for both short and long distances, say 1.5 euros or 3 euros, and see if the results still hold. The fact that drivers choose to donate under 1.35 euros but not under 1.80 euros may lie on the difference of 0.45 euros. Even though we do not find a difference in cash-out rate (thus, 1.80 euros don't attract drivers naturally more than 1.35 euros), the insignificance may simply be caused by a small sample size. Indeed, the

[18]We do not report tests comparing short-distance and long-distance ticket cash out and donate behavior under each treatment in this paper due to space limitations, but data is available upon request.

relatively small sample size for various treatments that we want to explore in the first stage may make some “would be" effects insignificant and increase the risk of bias, although we still found interesting patterns.

2.8 Conclusion and Policy Implications

Ridesharing for short-distance, daily commutes has gained importance in urbanization planning. Take the example of where the field is located. The French government expressed the wish to support and develop this solution as part of the public transportation system in the undergoing *Assises de la Mobilité*, at the end of which a new law of transportation will be settled.

Despite its potential in solving various problems in transportation, short-distance ridesharing faces difficulties in motivating people to use it. The current focus has been made mainly on monetary incentives (subsidizing passengers and drivers by offering passengers free trips and giving drivers extra bonuses). This paper argues that prosocial motivations should not be neglected, and if they are used properly, they may help to unblock cases where monetary incentives are dysfunctional or are too costly in the long run. An example would be extremely short-distance trips. Of course, monetary incentives are also present and should not be forgotten either, especially when trips are getting longer. A combination of monetary and prosocial incentives may be the proper way to promote daily ridesharing, but further investigations need to be made to better understand behavior under this emerging phenomenon.

Macro factors will also help for short-distance ride sharing. Adopting a new commuting habit is about cost and benefit but also about culture. Service providers should understand the operational and psychological costs for drivers and passengers, the particularities of daily ridesharing costs compared to long-distance ridesharing, which works well in lots of countries. Innovations anchored in service design that can reduce these special costs can help before playing with incentives. Policymakers, on their side, can also help reduce costs of adopting daily ridesharing by integrating ridesharing costs into public transportation subscription or by building reserved roads for ride-shared cars. Most importantly, by doing so, they are building the culture of ridesharing that will eventually create synergy with individual motivations.

CHAPTER 3
THE LIMIT OF MONEY IN DAILY RIDESHARING: EVIDENCE FROM A FIELD EXPERIMENT

Dianzhuo Zhu[1]

Abstract

The sharing economy has become a rising issue of concern these years because of the way that it reshapes traditional sectors and human interaction. Ridesharing is a leading sector in this phenomenon. Platforms have difficulties encouraging ordinary drivers to rideshare for short trips. Using high monetary incentives is a common strategy, but costly to maintain. In this paper, we show the limit of monetary incentives by conducting a field experiment in suburban villages next to Paris, based on the setting of a local ridesharing service. Drivers pick up passengers on their way. After the trip, they can decide to split their earnings between themselves and the charity. With 128 trips carried out under two compensation levels for drivers, 3 euros and 7 euros, we show that putting a higher monetary incentive has the same level of performance as a lower but sufficient one, both in terms of the rate of driver participation and of compensation claims. We argue that monetary motivations neither significantly "crowds out" nor "crowds in" non-monetary motivations in this scenario. We conclude that only strengthening monetary incentives may not be the most effective way to boost a short-distance ridesharing practice.

Keywords: Ridesharing, Monetary motivation, Field experiment

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[1]M&O-DRM Lab, University Paris-Dauphine, PSL Research University. The experiment has been registered in the OSF (https://osf.io/9us2j/) after the data collection but before the analysis process. The experiment is funded by *Parc Naturel Régional (PNR) du Vexin français*. However, all results reported are the author's personal opinion and do not necessarily reflect those of Ecov and PNR.

3.1 Introduction

Recent years have witnessed the rise of several so-called "sharing economy" platforms (Botsman & Rogers, 2010). Although its boundary lacks a universal agreement (Schor, 2016), ridesharing is, without a doubt, an essential component of this phenomenon. The world's first organized ridesharing among colleagues and neighbors appeared during World War II, initiated by the US government, in order to save war resources (Chan & Shaheen, 2012). Ridesharing forms have evolved ever since, had its ups and downs around the oil crisis in the 1970s, but have never been scaled-up as they are today. Two-sided platforms using information technology play a crucial role in the popularization of ridesharing, as well as in other sharing economy practices (Evans & Schmalensee, 2016).

Researchers are trying to understand different aspects of the sharing economy, among which we believe that understanding users' motivations, both monetary and non-monetary ones, is of great importance for three reasons. Firstly, platforms are only intermediaries for matching resources and skills between the two sides. Platforms themselves often do not own shared assets. The business models and codes are easy to replicate. In order to survive, the platforms must attract enough users to benefit from the network effect of one side of users attracting the other side (Shapiro, Carl, & Varian, 1998). This requires that the platforms better understand their users' motivations to join and to continue with the service. Secondly, the seemingly contradictory terms of "sharing", which is based on solidarity and caring, and "economy", which is based on the commercial system and is often related to a cool rationality, have triggered many ideological debates of what "true sharing" is.[2] Platforms who categorize themselves as sharing economy employ mixed strategies in practice. They evoke both the monetary benefits as well as the sense of belonging to a community. Understanding the interaction of the different

[2]An example would be the debate on whether Uber should be considered as being part of the "sharing economy". Some practitioners and researchers do not think so because Uber drivers use the platform to make a living, while ridesharing is based on matching non-professional drivers and passengers who happen to go to the same destination. The French governmental regulator excludes Uber from ridesharing. Uber is classified similarly to a taxi service, with a special denomination as VTC (*Véhicule de Tourisme avec Chauffeur* in French, which means "Tourist Vehicle with Driver). The same debates arise for the other platforms whose business models follow the same logic, such as spare room sharing. Other researchers would still like to treat quasi-professional platforms as "sharing economy", in the sense that they better utilize initially spare resources and that the matching problems are similar to "true" sharing economy platforms. These debates are part of the reasons why defining the scope of the sharing economy is difficult.

motivational triggers may help platforms to better adjust their strategies.

The last reason is related to the current state of the ridesharing sector. Although long-distance, inter-city ridesharing has had great success (represented by French company BlaBlaCar), short-distance, inner-city ridesharing companies still struggle to scale up.[3] The effort and time required for drivers to validate each trip remain a barrier. They usually need to download an app, enter the trip information, wait to be matched, possibly make a detour to pick up the passenger, ... for a small compensation. Current platforms are trying to solve the problem in two ways. On the one hand, they try to decrease the required effort by predicting the drivers' routines using machine learning techniques to match drivers with passengers automatically. Algorithms may help predict regular working commutes, but occasional trips are more difficult to be included. Meanwhile, off-peak hours are the least well served by public transportation, especially in rural areas. Ridesharing could be the right solution. On the other hand, the platforms could offer drivers higher monetary incentives to compensate for their efforts. However, it would not be financially sustainable for a platform, and could eventually have "crowd in" effects (B. S. Frey & Jegen, 2001), leaving only professional drivers on the platform, like Uber. Technology and monetary incentive both have their limits. Looking at the ignored side of non-monetary motivations of drivers could be another approach to support daily ridesharing with non-professional drivers.

This paper presents a small-scale field experiment in France to explore this question. The field setting ensures that the drivers can provide rideshares with the passengers with almost no extra effort. Two compensation levels are tested for the same trip. The compensation level is shown to the drivers before they pick up the passenger, but the set-up allows the drivers to decide whether they wish to receive the compensation or not privately after the trip. In the experiment, we add a dictator game during the compensation claiming phase, where we let drivers decide how much to put in their accounts and how much to donate to charity. Both monetary and non-monetary incentives are presented. The results show that the higher compensation level does not outperform the lower one, neither in participation enthusiasm nor in compensation collection behavior. We do not find evidence of motivation crowding for the different compensation levels.

[3]Here, we only consider ridesharing services that intend to attract occasional, non-professional drivers who also happen to go to the same destination as passengers. Taxi-like services like Uber are not included.

This paper is organized as follows: The next section gives a literature review on ridesharing and on related behavioral theories. Section 3.3 briefly introduces the field experimental set-up. Section 3.4 then raises the research questions and presents the experimental design. Section 3.5 analyses the experimental data and presents the robustness checks. Section 3.6 discusses the findings and Section 3.7 concludes the paper with some policy implications.

3.2 Literature Review

Since ridesharing has not scaled up until recently so the literature is relatively limited (see a historical review of Chan and Shaheen (2012) of North American ridesharing and a general review paper of Furuhata et al. (2013)), we expand our review to relevant papers on vehicle sharing in a general sense, like car sharing, hitchhiking and taxi-like sharing of personal vehicles such as Uber. Early papers on ridesharing motivations and behaviors are mostly published by researchers in transportation and other social science disciplines, who often use qualitative methods. For example, Shaheen et al. (2016) conducted 16 interviews with and collected 503 questionnaire responses of those who carpool on dedicated highways in the Bay Area, San Francisco. They highlighted that monetary and practical motivations come first than environmental and social ones. At about the same period, Shaheen et al. (2017) collaborated with the long-distance ridesharing platform BlaBlaCar and collected 618 survey responses. Monetary motivations are mentioned the most frequently by both passengers and drivers for all income levels, which is around 30% higher than the social and environmental motivations (ranked second and third for passengers and drivers, whose order switches for different revenue levels). Wilhelms, Henkel, and Falk (2017) conducted in-depth interviews with peer-to-peer carsharing participants. They found that economic interest, quality of life, being able to help others, and sustainability are the four leading motivations. Monetary motivations seem to be salient, but we still know very little about if it is the case in short-distance trips, and and if so, their extent.

Quantitative methods have entered the field of vehicle sharing only recently, as large-scaled observational data become more available on the successful platforms. Findings (mostly still working papers) are concentrated on Uber's users in the US. Topics include estimating the consumer surplus (P. Cohen et al., 2016), using the surge pricing strategy to increase the monetary incentives for high-demand places, and to observe their impact on drivers' working behavior (M. K. Chen, 2016), the gender pay gap (Cook, Diamond, Hall, List, & Oyer, 2018) and racial and gender discrimination (Ge, Knittel, MacKenzie, & Zoepf, 2016). In Europe, French researchers have collected data from long-distance ridesharing platform BlaBlaCar to study the drivers' pricing behavior. They showed that, controlling for the price level, more experienced drivers set a lower price level per seat, but can sell more seats than less experienced drivers. The drivers learn how to maximize their profit over time (Farajallah et al., 2019). These papers give insights into the effect of money. Indeed, in these cases, it makes sense to view drivers as profit maximizers who are sensitive to monetary incentives. However, for daily ridesharing among ordinary drivers, they may not be as receptive to monetary incentives, both because of the high effort cost per trip and because of non-monetary motivations.

Nevertheless, we can find substantial evidence on the relationship between monetary and non-monetary motivations in general human behavior research, which may apply to the case of ridesharing. One famous theory is the motivation crowding theory, which supposes that people can be motivated both intrinsically (not dependent on external consequences but driven by genuine personal interest) and extrinsically (dependent on external consequences such as prizes or sanctions) (Ryan & Deci, 2000). Extrinsic incentives such as offering money may "crowd out" the intrinsic joy, so that people refuse to carry out the task or no longer wish to carry out the same task once the extrinsic incentives are eliminated (Bénabou & Tirole, 2006; B. S. Frey & Jegen, 2001).[4] The theory has been tested and verified on many empirical cases. They point out the importance of not using extrinsic incentives to promote certain activities like picking up children after kindergarten (Gneezy & Rustichini, 2000) or donating blood (Mellström & Johannesson, 2008). At the same time, some other evidence shows that the "crowding-in" effect exists as well (Bolle & Otto, 2010). If the monetary incentive is high enough, the total participation rate will not be affected, or may even be higher. Meta-analysis confirms that both effects could exist, the direction depends on the message framing, available information, and other factors (Bowles & Polania-Reyes, 2012).

Another way of evaluating monetary and non-monetary motivations is by observing money

[4] "Crowding-out" is also applicable to extrinsic motivations ruining pro-social preferences such as fairness and ethics, which are difficult to be categorized as extrinsic or intrinsic.

splitting behavior. Experimental evidence shows that people are not always trying to maximize their profit. In the classic ultimatum game, people are given unconditional money and are required to split the money between themselves and another person. The recipient could potentially refuse the offer and make both sides earn nothing. People tend to give around 40% to 50% of their endowment to recipients (Thaler, 1988). Recipients are also willing to severely punish givers if they think that the split is unfair, with the threshold being 20% of the endowment (Levitt & List, 2007). In the classic dictator game, which is similar to the ultimatum game except that there is no risk of retaliation of recipients, dictators still choose to share around 20% of the endowment with recipients (Forsythe, Horowitz, Savin, & Sefton, 1994; Kahneman, Knetsch, & Thaler, 1986). Whether it is because of inequity aversion (Fehr & Schmidt, 1999), altruism (Andreoni, Harbaugh, & Vesterlund, 2008) or the warm glow (Andreoni, 1989), non-monetary motivations play an important role in decision making.

However, the degree of non-monetary motivations may change as the setting of the game changes. As it is relevant to the design of the experiment in this paper, we briefly review three settings for dictator games: the identity of the recipient, stake, and effort. By merely introducing the last name or letting dictators see the face of the recipient significantly increases the amount given to the recipient compared to an anonymous recipient (Burnham, 2003; Charness & Gneezy, 2008). Charities are also seen as "more deserving" to receive a higher split compared to anonymous recipients (Eckel & Grossman, 1996). The effect of the stake is less clear. Some have found evidence, while others have not. However, a meta-analysis shows that the willingness to give decreases as the stake increases (Engel, 2011). In the basic setting of dictator games, the endowment is given to dictators as a gift. However, when dictators need to put in effort to earn money, such as by completing a task or by outperforming others in a test, the willingness to share money with recipients drops compared to receiving a windfall (Cherry, Frykblom, & Shogren, 2002; Hoffman, McCabe, Shachat, & Smith, 1994; List, 2007).

3.3 Introduction of the Field Set-up

The experiment is in collaboration with a French start-up, Ecov, which aims to use ridesharing to solve partially the transportation problems in suburbs and rural villages. In these areas, massive public transportation is inefficient. The population density is too low for the current bus and train lines to be sufficiently occupied and profitable. At the same time, too few lines are deployed to satisfy the diverse needs of residents. Facing this dilemma, families living in these areas prefer to own cars, which in turns reduces the efficiency of public transportation and causes other problems such as pollution, wasted seats, and traffic jams.[5] Ridesharing, as a complement to public transportation, could be an on-demand solution for these areas to reduce cost and to solve related social and environmental issues. Ecov collaborates with local governments to build ridesharing stations in their villages. Each station is composed of a ticket machine (see Appendix B.1), a pick-up point next to the machine, which is usually a dedicated parking slot, and electronic information screens. By the end of April 2018, Ecov has built 32 stations in 6 different regions in France.

Stations are usually close to the residential areas, or public transportation stops, in order to ensure a constant flow of vehicles and easy access for passengers. A passenger who wishes to rideshare goes to the station and enters her planned destination. The machine then prints a ticket with a compensation level (see Appendix B.2). Once the request is made, it is shown on the information screens which are usually located several hundred meters in front of the station.[6] For a demonstration of what a request looks like, see Appendix B.3.

All passing drivers would then see the request on the screen first and the passenger afterwards. If they happen to drive towards the same destination, they can stop and pick up the passenger. The effort needed for the drivers is minimized in this setting. At the end of the trip, the passenger is supposed to give the ticket to the driver. The driver can freely decide whether she wants to cash out the compensation indicated on the ticket. If so, she needs to go to the website of the service and enter the 4-digit code on the ticket. If she does not cash out, the money is not be given back to the passenger.[7] The compensation for the drivers is 9 cents per kilometer per passenger.

[5]In the region where the experiment takes place, 80.7% of families own cars, and 30.7% own more than one car (Source: *Équipement automobile des ménages en 2014 : comparaisons départementales*, INSEE.)

[6]Some stations have several screens if the station is by the main road with several feeder roads before. Some stations have screens on each side of the road.

[7]The company receives all the uncashed compensations. In a standard setting, passengers pay their ride, but in the experiment, all tickets are paid by the experimenter. More details are given in the next section.

3.4 Research Questions and Experimental Design

In this section, we firstly raise two questions that we wish to answer in this paper, both of which are related to the general research question: Are monetary incentives effective for daily ridesharing? We then present the design of the experiment and list the possible outcomes of the research question since we cannot predict the answer for the moment.

3.4.1 Research Questions

Historical data of the company (Ecov) suggests that non-monetary motivations play a role - only around 20% drivers eventually cash out their money. This could be explained by various reasons such as the laziness to cash out or insufficient monetary incentives. However, we cannot neglect the possibility that some drivers are willing to help passengers without having to be paid. To confirm the intuition, we examined the archives of interviews, questionnaires, and field reports. We also carried out several field trials. Most of the time, when asked the reason why they stop and pick up passengers, drivers would mention "solidarity" or "pleasure to help". Not only in these declarations but also field trials, we witnessed drivers who refuse to accept the ticket because they "do not want to be paid and will not cash out in any case".

We now wish to explore further what role non-monetary incentives play and whether monetary incentives have limits. Two questions are asked: Q1: Will a higher compensation increase participation? and Q2: Will a higher compensation trigger a more active cash-out behavior?

3.4.2 Experimental Design

The process of the experiment is adapted from previous experiments (D. Zhu, 2017). We choose two villages, A and B. Each has a ridesharing station. The distance between A and B is about 25 kilometers. Since we wish to observe the drivers' behaviors and control as many variables as possible, we hire people to make rideshare requests as passengers. From May 2017, we start hiring passengers among university-level students close to the villages using online and offline job posts. Five passengers are hired, and 4 of them, two men and two women, eventually participated.[8] Passengers are between 18 and 19 years of age. Before the experiment, they are given a briefing about the steps to follow. They are informed that they could ask us questions during the experiment period if they are not sure about some details. From June to July 2017, during the daytime, they are assigned to make ridesharing requests between the stations of village A and village B.[9] For the ease of the organization, some trips are from village A to village B, and some are from village B to village A.[10] Each request has only one passenger to control the compensation level.

With each request, the destination, number of passengers, and compensation level are shown on the screen.[11] The compensation level is randomly chosen to be either 3 euros or 7 euros.[12] Since it is shown on the screen, the drivers would know how much they could earn before making a decision. The same amount is also printed on the ticket. Once a driver stops, the hired passenger embarks into the car and rideshares with the driver just like a normal passenger. At no moment of the trip does the passenger reveal the fact that she is a "fake" passenger, in order to obtain the natural behavioral data of drivers.[13] Meanwhile, the passenger needs to chat with the driver naturally to gather extra information. At the end of the journey, the passenger should give the ticket to the driver and make clear that the driver can choose either to cash out the 3 (or 7) euros or to donate the compensation to a charity (donation option is also printed on the ticket,

[8]The fifth hired passenger starts quite late and only makes two trips without following the protocol. We thus decide not to take her trips into account.

[9]All trips are made between 8 a.m. and 8 p.m., including both weekdays and weekends. Passengers are assigned to different time slots during the week to randomize external variables such as passenger characteristics, weather, hour of the day, day of the week. If a regular passenger wishes to use the service, the hired passengers should wait until that passenger finishes.

[10]Most of the trips were done from village A to village B since the waiting time is shorter for this direction. Passengers could take buses from village B back to village A if needed. We discuss the potential bias in the data analysis section.

[11]In the experiment, we use *EMMENEZ 1 PASSAGER A [village A/B], GAGNEZ 3/7 €* (see Appendix B.3 for a demonstration) to inform drivers to "take a passenger to village A (or B), and earn 3 (or 7) €". We designed a questionnaire before the experiment to choose the best wording of the screen message. Among the three versions, the selected one had the highest score of understanding.

[12]We choose these two compensation levels for a reason. Three euros is higher than the normal price level of the service, which is 2.3 euros. We choose 3 euros to make the incentive an integer and no lower than the initial one. Seven euros is close to the upper price limit for trips to be considered as ridesharing in France, above which the drivers need to pay tax for the amount earned. Seven euros may not seem to be a very high stake, but it still more than doubles the lower one. If we put an unusually high price, whatever effect of that price would not be of relevance for practical usage, not to mention the potential regulatory issues in practice.

[13]Some drivers, after having passed by or even participated several times, ask why they see different compensation levels. Some of them deduce that the service was trying to test different compensation levels. Even so, they are not suspicious about the identity of passengers. The hired passengers are also briefed about how to answer some potentially tricky questions.

see Appendix B.2). The driver is also informed that she could as well choose not to accept the payment at all, but even in this case, the money is not returned to the passenger.[14] Even though this information is written on the ticket, the passenger orally informs the driver, in case that some drivers do not read the tickets. The passenger always leaves the ticket in the car, even if the driver claims not to accept the money. After each trip, the passenger fills out a questionnaire with a set of information that may help analyze the data.[15]

After each trip, the driver has 14 days to decide what to do with the ticket. If she eventually decides to go to the website, she will face the choice of splitting the compensation between her account and a charity, as shown in Appendix B.4.[16] She can choose to keep any amount between 0 and the entire compensation for herself. Only if the personal and the charitable accounts sum up to the compensation level is then choice validated. The money split choice remains private. The passengers do not know where the compensation goes, and do not receive the uncashed amounts. The drivers' decisions are not published online either. Only the employees of the company and the experimenter could observe the drivers' behavior. Since we are total strangers to the drivers, social pressure should not be an overwhelming concern in the latter's decision making.

We add a dictator game phase with the charity as a recipient instead of merely letting drivers cash out the entire amount, for three reasons. Firstly, looking at the participation rate only cannot help us distinguish crowding-out and crowding-in effects. We need to observe how much interest drivers have on the compensation they receive. Secondly, we introduce the charity as a recipient to neutralize the social gaze effect. If the passenger can receive the split compensation,

[14]In fact, the money from the rejected tickets is shared between the company and the local government. However, during the trip, the drivers are not informed about where the money goes exactly. They could ask the service for an answer.

[15]See Appendix B.5 for an English version of the questionnaire (the original version is in French). To answer the questions, the passengers either observe (such as gender of the driver) or chat with the driver (such as their motivations). The passengers are not required to reply to all the questions, but the only maximum possible. Since the drivers do not need to register to participate, if they do not deal with tickets, we will have no information about them. These questionnaires thus help us to collect essential information about the drivers for bias checking. They also offer complementary qualitative information to which we sometimes refer to in the paper, such as the declared motivations of and other conversations with drivers.

[16]The charity we chose for the experiment is the same as in the previous paper (D. Zhu, 2017): *Les Restos du cœur*. This association aims to give free food to people in need. We choose it because it is of general interest, without particular political or religious preferences, well-known and well-respected in France. So the charity preference bias could be minimized. The name of the charity does not appear on the ticket, but only appears on the money split web page. This design is also to minimize preference bias before going to the website. Due to operational constraints, we cannot make a list of several charities and let drivers choose.

the percentage that drivers give up would be upwardly biased by the social interaction with passengers. This does not make much sense as the service could simply charge passengers less. The last reason is the practical side. Introducing charity may increase the overall ticket claim rate, according to the literature. As we would like to have more identified drivers to have more precise driver information and that only by claiming are drivers identified, adding a charity would be a good choice.

3.4.3 Hypotheses

Q1: Will a higher compensation increase participation?

If some drivers with intrinsic, non-monetary motivations are in general crowded out by a higher compensation level, the overall waiting time for trips under 7 euros would be longer than trips under 3 euros, because fewer drivers would be willing to pick up passengers at 7 euros. If neither crowding-out nor crowding-in effect exists, the two compensation levels will perform similarly in terms of the passenger waiting time. If monetary incentives do crowd in participation, the waiting time with 7 euros would be lower than with 3 euros. However, if crowding-out and crowding-in effects both exist and cancel out, the overall waiting time would not differ either. We then need to look at the money split stage.

Q2: Will a higher compensation trigger a more active cash-out behavior?

Here, we design a dictator game with the charity as a recipient to let drivers reveal their preferences for the money distribution. We then analyze the distribution of the money split decisions under different price levels. This behavior is closely related to the motivation crowding effects discussed above. Whether the crowding-out or crowding-in effects prevail, if the drivers with 7 euros are more money-oriented than with 3 euros, then we would expect to observe a higher percentage of drivers who cash out. Only when no motivation crowding effect occurs could we say that drivers are indifferent when facing 3 euros and 7 euros. The same proportion of drivers would like to cash out. Nevertheless, it is not easy to predict if they would cash out a higher proportion of the endowment as the compensation increases. Drivers may cash out a higher proportion under 7 euros, but they may also stay with a “fair” proportion.

3.5 Results

3.5.1 Summary Statistics and Randomization Check

At the end of the experiment, 128 valid observations are collected, among which 57 are of 3 euros, and 71 are of 7 euros. Each valid observation is a successful trip, meaning that a hired passenger is picked up by a driver and that the passenger respects the behavior protocol. Table 3.1 reports the summary statistics and tests if key confounding variables are well balanced between the 3-euro and 7-euro groups.

Most variables can be seen as being randomly attributed to the two groups. The majority of trips depart from village A. We hire two male and two female passengers, but the female passengers work for longer than the male ones and contribute 74 trips. In terms of drivers, however, only 46 trips are made by female drivers. Without knowing the overall driver gender distribution in the region, we cannot conclude that male drivers are more motivated for ridesharing. A median driver is 30-45 years old. The hired passengers are between 18-19 years of age. We carefully control this. 70 tickets out of 128 are claimed, with 66 partially or entirely cashed out, and 8 partially or entirely donated. We can only know for sure the driver's identity if they claim their tickets. In the end, 49 drivers are identified (some drivers claimed several tickets), with 19 female and 30 male, which is similar to the gender distribution for all trips.

The only doubt lies on the variable "new driver", where there are slightly more frequently seen for 7-euro trips ($p = 0.093$). New drivers are those who participate in the experiment for the first time. We know that either by the drivers' statement if they never claim tickets or by their ticket claim record. Since the design of the experiment does not exclude multiple participation of the same driver, it is an important variable to control for post hoc. Here, we cannot draw the conclusion that 7-euros attracts more inexperienced drivers to participate: we analyze this factor in more detail later on.

3.5.2 Analysis

We now take a closer look at the participation and ticket claims to answer the two questions asked earlier in the article.

Table 3.1: Summary Statistics

	All trips	3-euro trips	7-euro trips	Binomial 2-sided test
Total trip number	128	57	71	0.250
Departing from village A	112	52	60	0.509
With female passengers	74	32	42	0.295
With female drivers	46	26	20	0.461
With "new" drivers	91	37	54	0.093*
Ticket cashed out (partially or entirely)	66	27	39	0.175
Ticket donated (partially or entirely)	8	3	5	0.727
Driver median age group	30-45	30-45	30-45	
Number of first sign-ins during exp	49	19	30	0.152
Among whom are female	19	8	11	0.648
Identifiable drivers' mean age	38.12			
	(12.3552)			
Total passenger number	4			
Among whom are female	2			
Passenger mean age	18.38	18.47	18.31	
	(0.6887)	(0.7584)	(0.6232)	

Notes: Standard errors are reported in parentheses. The binomial 1-sided test is for testing differences in the frequency between 3-euro and 7-euro subgroups. "New drivers" are drivers who only participate once in the experiment or the first participation of drivers who participate several times. We count the number of participations only based on observed data, not on declarative data. If a driver cashes out or donates more than once using the same account, we can be sure that the driver participates more than once. If a driver declares that he/she participates during the experiment, but we have no direct proof of who the driver is, then we still treat the trip as carried out by a new driver. This method may lead to an underestimation of the number of repeat drivers. Data for six trips on this variable are missing, among 128 total trips. Identified drivers are those who signed in to the website with the associated code so that we can connect the trip with the person. Each number of first sign-ins (including creating new accounts) is connected to an identified driver. This also provides us with the correct information on gender, age, and previous experience with the service. Identified drivers could participate several times, so that the total number, 49, is lower than the ticket treatment frequency.

*** p<0.01, ** p<0.05, * p<0.1

Q1: Will a higher compensation increase participation?

From the data we have, the answer is no. Increasing the price from 3 to 7 euros will neither encourage nor discourage participation.

Table 3.2 presents the descriptive statistics on driver participation and tests of distribution. We use two ways to measure the driver participation: the waiting time and the number of passing cars before a driver stops.[17] What we are interested in is if these two measurements differ significantly under the different compensation levels. If so, whether the drivers show

[17]Here, we only ask passengers to count the vehicle types that are available for ridesharing, i.e. buses, trucks, professional cars, cars from driving schools etc. are excluded from the counting.

more enthusiasm to participate under one compensation level than another.

Both measurements have their advantages and disadvantages. Since our experiment covers different time periods during the day, the waiting time is straightforward, but could vary a lot depending on the actual traffic flow and random appearance of interested drivers. The number of passing cars bypasses the disadvantage of being restricted to participating drivers by measuring the participation rate among the entire population of potential drivers. From the table, we can see that the medians are reasonable (around 15 minutes and 35 passing cars). However, the upper and lower extremes indicate a highly variable sample. Sometimes the first passing driver stops, whereas some times the passenger needs to wait one hour. We understand that there are many nonhuman factors that could affect these measurements, but with randomness and 128 observations in total, we can still compare if different compensation levels follow the same pattern of distribution. The Kolmogorov-Smirnov test on the waiting time ($p = 0.569$) and Wilcoxon rank-sum test on the passing cars ($z = 0.877$) show that there is no significant evidence to reject the same distribution hypothesis.

We also test the difference in the distribution of the waiting times and the number of passing cars for five subgroups in which drivers may react differently to price. The departure villages may contain different driver pools, although our hypothesis is that drivers are homogeneous. The drivers who claim tickets and male drivers may, in general, be more sensitive to price. The drivers may be more selective if the passenger is male. When passengers use the hitchhiking gesture (i.e. a fist with an up-turned thumb), they may appear prominent to the drivers. Our tests show that neither the waiting time nor the number of passing cars are significantly different between 3 euros and 7 euros conditional on any of these variables.

Recall from the previous analysis that when participation does not differ, it could either be no motivation crowding effect at all or that crowding-out and crowding-in effects cancel each other out. We then need to compare the ticket claim behavior to clarify this. The next subsection examines this in detail.

Table 3.2: Driver Participation Measured by Waiting Time and Number of Passing Cars

	All trips	3-euro trips	7-euro trips	K-S test	Sample size
Waiting time (in minutes)				0.569	128
Mean	18.95	19.60	18.4277		
Std. err	(15.1192)	(14.9593)	(15.3325)		
Median	14.73	15.63	14.3		
Min	0.25	0.25	0.63		
Max	75.02	56.55	75.02		
Waiting time: depart from village A				0.739	112
Waiting time: for claimed tickets				0.269	70
Waiting time: for male passengers				0.856	54
Waiting time: for female drivers				0.952	46
Waiting time: for trips using gesture				0.370	38
				Wilcoxon rank-sum test	Sample size
Number of cars passing by beforehand				0.877	128
Mean	85.18	87.36	83.44		
Std. err	(112.0514)	(112.027)	(104.2558)		
Median	35	38.5	32		
Min	0	0	2		
Max	486	486	367		
Number of cars: depart from village A				0.5369	111
Number of cars: for claimed tickets				0.8220	70
Number of cars: for male passengers				0.5258	53
Number of cars: for female drivers				0.5872	45
Number of cars: for trips using gesture				0.4780	38

Notes: The Kolmogorov-Smirnov test examines if the 3-euro and 7-euro trips follow the different distribution of waiting time (continuous variable). For the number of passing cars, we consider it as a discrete variable and use Wilcoxon rank-sum test for the difference of distribution.

*** p<0.01, ** p<0.05, * p<0.1

Q2: Will a higher compensation trigger a more active cash-out behavior?

We do not observe a significant difference in deciding whether to cash out or to donate tickets nor how to split money differ under the different compensation levels. Together with the similar participation behavior presented above, we believe that the drivers are of the same type under the 3-euro and 7-euro incentives. The drivers who claim tickets often choose to keep the entire endowment themselves, which is in line with the findings of earned versus windfall money. The drivers seem not to be interested in using the charity donations to signal their prosociality to themselves. Maybe it is because helping to pick up a passenger without asking for money is a strong enough prosocial signal itself.

Table 3.3 presents the number of drivers at each split point. Even though the money could be split at any amount up to two-digits after the decimal, all drivers choose to split at integer values. For the 3-euro tickets, 27 drivers choose not to claim their tickets. The same number choose to cash out the entire 3 euros. Only three drivers donate, and they all donate the entire amount. The situation is a bit more complicated for the 7-euro tickets. Thirty-one drivers abandon their ticket, while thirty-four drivers cash out the entire amount. Among the rest five who donate partially, the amount donated covers 1,2,4 and 7 euros. It is clear that while implicit donation (i.e. not claiming tickets) is common, explicitly signaling prosociality through donating to charity is very rare, both under 3 euros and 7 euros.

Table 3.3: Number of Trips For Each Compensation Split Decision

	3 euros	7 euros
Not claimed	27	31
Cash out 0 euro (donate all)	3	1
Cash out 1 euro	0	0
Cash out 2 euros	0	0
Cash out 3 euros	27	1
Cash out 4 euros		0
Cash out 5 euros		1
Cash out 6 euros		2
Cash out 7 euros		34
Total number of trips	57	71

Figure 3.1 presents the cumulative distribution function of the ticket claim behavior in absolute amounts (left) and in the percentage of compensation level (right). Here, we only show the 70 claimed tickets. 7 out of 7 euros cashed out means that 100% of the entire compensation is cashed out. The Kolmogorov-Smirnov test on the percentage cashed out shows that the two curves for 3 and 7 euros follow the same distribution $[D = 0.075, p = 1.000]$.

To further analyze if the ticket claim decision differs when the compensation level changes, we run several regressions with the main possible confounding variables controlled. Using the trip information database and the complementary questionnaire information collected by the passengers, we have data on various aspects that may possibly be biased. The next few tables

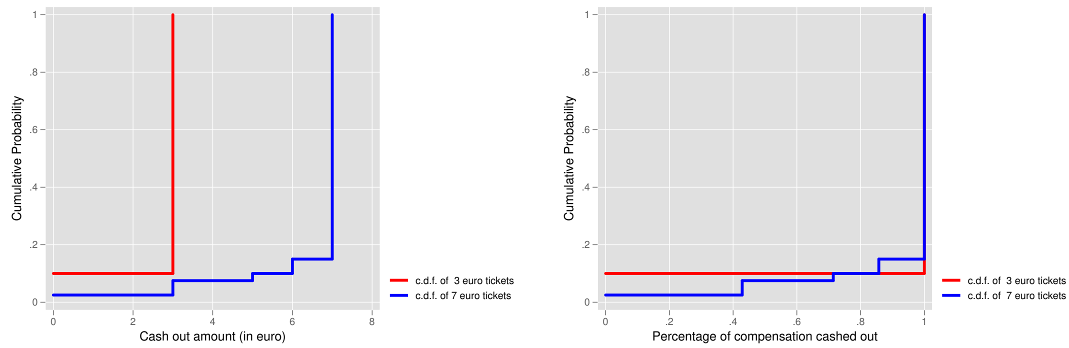

Figure 3.1: CDF Plot of Cashed out Amount and Percentage For 3 € and 7 € (All Claimed Tickets Included)

present the findings. For each table, we run multiple regressions with six groups of variables. The first column is the base case, with only the treatment variable (compensation level) and repeat/new driver indicator, which are significant at the 10% level in their summary statistics. Column 2 adds the passenger and driver profiles. Column 3 regresses on the measurements of the drivers' knowledge of the service. Column 4 and 5 regress on the monetary and major non-monetary motivations using different measures of monetary incentives. Column 6 includes other auxiliary variables. We first take as the dependent variable the binary variables "if cashed out partially or entirely" (Table 3.4) and "if donated partially or entirely" (Table 3.5) on these subgroups using the probit model. Since the donation decision is very rare (only 8 tickets are donated), we also report the results for the Personalized Maximum Likelihood Estimation (PMLE), developed by (Firth, 1993), in Table 3.6 to correct for rare events.

Table 3.4 shows that the ticket compensation level has no significant effect in deciding if a driver would cash out the ticket or not. What matters most is the driver's previous experience of the service. If a driver has already participated, or has heard of the service, the chance of cashing out increases. When we regress on the drivers' knowledge of the service, the past experience is no longer significant, since experienced drivers already know how the service works.[18] Another interesting finding is that the drivers of male passengers cash out less often. One explanation is that a male passenger has more difficulties finding a ride so that the drivers who are willing to pick them up are more enthusiastic about ridesharing and less interested in a

[18]Experienced driver and has heard of service/knows how it works are not strongly correlated, since other drivers who have never participated before may also have heard the service or know how it works. That is why the effect of the experienced driver variable is absorbed by the driver knowledge variables in column 3.

monetary reward. The descriptive table shows that the driver experience and passenger gender are generally distributed equally between the 3-euro and 7-euro trips.

Table 3.5 and 3.6 report the same results, except that in column 3, repeat drivers are slightly less likely to donate. The treatment variable "compensation level" is again not significant in any case. We added the variable "gesture" in analyzing whether or not to donate. It is only slightly significant and is equally distributed for the 3-euro and 7-euro trips. The result is consistent with our intuition: the drivers who stopped with an idea that the passenger is a hitchhiker are more likely to donate money to charity, even if they have seen the screen and price beforehand.

We now turn to the analysis of if the percentage of ticket claim (cash-out or donation) changes with the scale of the monetary incentive. The underlying logic is that even if the drivers behave similarly in deciding whether or not to cash out or donate, they may choose to keep different proportions of the compensation when compensation level increases, for that their motivations could also differ. We already see from the previous CDF plot that the distributions of the cash-outs and donations do not differ. Anyway, most of the decisions are clustered near the lower bound of 0% and the upper bound of 100%. Nevertheless, we still present some regression results here to confirm our hypothesis.

We consider the cash-out and donation percentages as continuous variables, even if they only have limited values here. Since they are bounded variables, we use the Tobit instead of OLS regression for more precision. Table 3.7 presents the results on the cash-out percentages and Table 3.8 presents results on the donation percentages. The results are not surprising: none of the explanatory variables are significant, except a slight positive significance at 10% level on "driver heard of service only" in the cash-out table. However, the drivers' knowledge of the service is balanced between the two groups. The treatment variable, the compensation level, is never significant.

To summarize, the drivers' ticket claim decisions do not differ when compensation level changes from 3 euros to 7 euros. The claim decision includes whether or not to cash out, whether or not to donate, as well as the proportion of the entire amount to cash out and to donate. The results hold even if we control various possible factors, especially when for repeat/new drivers, for which we had some suspicions at the beginning of the analysis that it might have an impact. Together with the results of the previous sections that the drivers' participation does not differ either, we can deduce that the two compensation levels attract the same type of drivers. Thus, a higher monetary incentive neither crowds out more prosocial drivers nor crowds in more selfish drivers. Money has a very limited effect in this spontaneous ridesharing setting.

3.6 Discussion

We observe that for the compensation levels of 3 euros and 7 euros, the drivers who participated are of the same type and behave similarly. The same proportion of drivers claim their tickets, and these drivers show a similar pattern of money split decisions. The result is quite robust after controlling several potential biases. On the one hand, the majority of drivers who claim tickets to cash out the entire compensation, which is in line with the literature that reports low generosity levels when the endowment is earned rather than given. Even though the literature asserts that charities are a more "deserving" recipient than an anonymous recipient, this earned-money effect persists even when we introduce a charity as a recipient. The drivers do not show much enthusiasm for donations. The donation rates (including partial donations) for 3 euros and 7 euros are 5.26% and 8.45% respectively (or 10% and 15% if we only consider the claimed tickets). Though many drivers found it a to be "good idea" to have the donation option, their attitudes towards donations did not necessarily translate into decisions.

We should not ignore that close to half of the tickets are neither cashed out nor donated, both for the 3-euro and for 7-euro tickets. These drivers do not go through the dictator game process, but they can also be considered to have voluntarily given up their endowment. It is difficult to know the exact reason why they do this. They may have forgotten the ticket after the trip. They may be altruistic and do not want to put ridesharing into a monetary system. They may initially not be opposed to the idea of cashing out, but since they had a great time chatting with passengers, they prefer not to think about the ticket and keep the experience as a social one. There may be several reasons at the same time.

Whatever the reasons are, the percentage of the endowment abandon is much higher than what we would observe in a laboratory setting. More interestingly, this inertia to monetary incentives does not change even if the compensation level is more than doubled from 3 euros to 7 euros. A higher monetary incentive seems not to be able to transform a money-insensitive person into a money-sensitive one, nor could it bring in more money-sensitive people. What the money does achieve here is that it successfully splits the people into two types: Those who are money insensitive and would not claim their tickets at all or would donate them; and those who are money sensitive would cash out the entire amount, whether it is 3 or 7 euros. We hope that the randomization of the compensation levels, the time of the day/week for the rideshare requests and the passenger profiles have succeeded to minimize the effect of all of these uncontrollable variables.

Of course, the experiment has its limits. Although we attempt to control a maximum number of factors, by hiring passengers with similar profiles (local young students) and by carefully briefing them, there are other factors that we could not control. We could not control the weather, though luckily, the weather did not change much during the experimental period from June to July. We could not control for the requests to be made at the same hour of the day as the experiment would have taken too long. We could not control the waiting time since it entirely depends on the decision ofthe passing drivers. We could also not control for the occasional technical problems or other experimental uncertainties.

Despite these limitations, we devise adapted methods to reduce the bias and increase the control over the experiment. Unlike most field experiments, we are not able to pre-assign drivers into experiment and treatment groups. This is also what makes the setting interesting. However, by asking hired passengers to observe and to chat with drivers, we could still obtain essential knowledge of the driver profiles, and even more. This information then helps us to carry out the randomization and bias checks. Because of the budget constraints, we only collect 128 valid observations, which is quite small-scaled compared to many other field experiments. However, these are 128 individual decision-making observations under similarly framed situations without attrition, which makes them reliable data. Also, the behavioral similarity under the different compensation levels prevails, even after controlling for many factors. We believe that this experiment provides interesting insights and fills a gap in the quantitative analysis of the limited role of monetary incentives in the ridesharing sector.

3.7 Conclusion

We conduct a field experiment with a spontaneous ridesharing service in the suburbs of Paris. We test a 25 km trip with 3 euros and 7 euros as the compensation. We find that drivers for 3 euros and 7 euros behave similarly in terms of efficiency (participation enthusiasm as measured by the waiting time) and sufficiency (compensation cash-out enthusiasm as measured by a dictator game). No motivation crowding effect takes place. Both money-oriented and non-money-oriented drivers would pick up passengers, but the money-oriented drivers would cash out the entire compensation, whether it be 3 euros or 7 euros.

We believe that the barriers to the success of the daily ridesharing may not be due to the lack of monetary incentives per se. Short distance platforms often use the lure of money to encourage non-professional drivers, but if the effort that drivers need to make in order to pick up passengers successfully is too high, the drivers would end up being professional and would only respond when the monetary incentive is high enough. We show in this experiment that once the effort barrier is eliminated, a moderate compensation (3 euros) would be sufficient for non-professional drivers to rideshare during their daily trips. A higher monetary incentive (7 euros) does not perform better than the moderate but still sufficient one. Theories in two-sided platforms also suggest that the side which benefits more from the platform (in this case, the passengers) should be charged more (Rochet & Tirole, 2004). In this case, it is the passenger who puts in more effort to go to the station and wait. This experiment demonstrates the limit of money incentives and offers strategic implications on how daily ridesharing service providers could attract non-professional drivers.

Table 3.4: Drivers' Cash-Out Decision Analysis: Probit

Dependent variable = cashed out partially or entirely (binary)

	(1) Basic	(2) Profile	(3) Knowledge	(4) Motivation-1	(5) Motivation-2	(6) Others
Compensation level	0.0459	0.0364	0.0665	0.0384	0.320	0.0287
	(0.0582)	(0.0609)	(0.0626)	(0.0597)	(0.197)	(0.0645)
Has participated during exp	0.495*	0.557**	-0.419	0.382	Omitted	0.258
	(0.270)	(0.282)	(0.395)	(0.284)		(0.301)
Male passenger		-0.546**				
		(0.237)				
Male driver		0.176				
		(0.248)				
Driver age group		-0.0220				
		(0.132)				
Driver heard of service only			1.033***			
			(0.324)			
Driver knows how it works			0.711*			
			(0.384)			
Declared monetary motivation				0.362		
				(0.286)		
Declared social motivation				-0.174	-1.214	
				(0.259)	(0.785)	
Declared motivation on solidarity				-0.372	0.544	
				(0.240)	(0.684)	
Days waited until cash-out					0.339	
					(0.395)	
Driver saw price on screen						0.181
						(0.264)
Number of children in the car						0.539
						(0.368)
Number of empty seats before trip						0.176
						(0.157)
Weather						0.110
						(0.193)
Constant	-0.261	-0.0503	-1.191***	-0.0417	-0.146	-0.829
	(0.340)	(0.437)	(0.430)	(0.381)	(0.851)	(0.655)
Observations	122	122	122	121	49	105
Pseudo R^2	0.023	0.057	0.158	0.053	0.273	0.049

Notes: Standard errors in parentheses. Column 1 shows the basic regression result with only treatment and control of within-group drivers. Column 2 adds the passenger and driver profiles. The passenger age is not reported in any of the regression tables because it lacks variation as we control the age of passengers to be between 18 and 19 years old. The driver age groups are estimated by the hired passengers: 1=18-30, 2=30-45, 3=45-60, 4=>60. For the weather, 0=sunny/good weather, 1=cloudy, 2=rainy/other bad weather. For the identified drivers, we correct any possible mistakes by using their declared age during registration. Column 3 regresses on the measurements of the drivers' knowledge of the service. Columns 4 and 5 regress on the monetary and major non-monetary motivations. The difference is that column 4 uses declared monetary motivations based on the passengers' questionnaire responses, while column 5 uses the days waited between the rideshare and cashing out as a proxy to measure how "eager" the driver is for the money. As only cashed out tickets have this data, so the number of observations decreases dramatically compared to other regressions. Column 6 includes another auxiliary variable: "drivers saw the price on the screen" is a declared variable from the questionnaire, which may contain driver comprehension bias and measurement errors, though we include it here to check if some drivers stop without noticing the compensation level. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Drivers' Donation Decision Analysis: Probit

Dependent variable = donated partially or entirely (binary)

	(1) Basic	(2) Profile	(3) Knowledge	(4) Motivation-1	(5) Motivation-2	(6) Others
Compensation level	0.0182	-0.0172	0.0253	0.0362	0.0252	0.0442
	(0.0955)	(0.101)	(0.0995)	(0.102)	(0.120)	(0.119)
Has participated during exp	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Male passenger		-0.0693				
		(0.400)				
Male driver		0.791				
		(0.493)				
Driver age group		0.0808				
		(0.220)				
Driver heard of service only			-0.0483			
			(0.490)			
Driver knows how it works			0.731			
			(0.469)			
Declared monetary motivation				-0.487		
				(0.608)		
Declared social motivation				0.0103	-0.205	
				(0.480)	(0.526)	
Declared motivation on solidarity				-0.351	0.0342	
				(0.417)	(0.481)	
Passenger used gesture				0.781*	0.860*	
				(0.405)	(0.458)	
Days waited until cash-out					-0.0468	
					(0.0684)	
Driver saw price on screen						-0.428
						(0.459)
Number of children in the car						Omitted
Number of empty seats before trip						0.121
						(0.309)
Weather						-0.339
						(0.425)
Constant	-1.452***	-1.973**	-1.692***	-1.635**	-1.351*	-1.685
	(0.552)	(0.795)	(0.611)	(0.645)	(0.717)	(1.203)
Observations	91	91	91	91	49	66
Pseudo R^2	0.001	0.061	0.058	0.082	0.099	0.042

Notes: Standard errors in parentheses. The six columns in the table follow the same logic as Table 3.4. Note that experienced drivers are excluded here, meaning that none of the experienced drivers ever donated. The number of children is also omitted since all drivers who donated have no children in their cars. Only 8 out of the 128 tickets have been partially or entirely donated. We use the Personalized Maximum Likelihood Estimation (PMLE) method (Firth, 1993) to correct for this rare event bias. The results are presented in Table 3.6.

*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Drivers' Donation Decision Analysis: PMLE Rare Event Correction

Dependent variable = donated partially or entirely (binary)

	(1) Basic	(2) Profile	(3) Knowledge	(4) Motivation-1	(5) Motivation-2	(6) Others
Compensation level	0.0234	-0.0234	0.0514	0.0354	0.0187	0.0433
	(0.179)	(0.181)	(0.182)	(0.180)	(0.192)	(0.208)
Has participated during exp	-1.837	-1.986	-2.754*	-1.678	-1.911	-1.388
	(1.470)	(1.473)	(1.517)	(1.480)	(1.485)	(1.471)
Male passenger		-0.0202				
		(0.720)				
Male driver		1.259				
		(0.918)				
Driver age group		0.155				
		(0.394)				
Driver heard of service only			-0.0725			
			(0.925)			
Driver knows how it works			1.279			
			(0.843)			
Declared monetary motivation				-0.464		
				(0.960)		
Declared social motivation				0.215	-0.101	
				(0.797)	(0.820)	
Declared motivation on solidarity				-0.519	0.0958	
				(0.725)	(0.772)	
Passenger used gesture				1.302*	1.257*	
				(0.712)	(0.729)	
Days waited until cash-out					-0.0409	
					(0.104)	
Driver saw price on screen						-0.673
						(0.816)
Number of children in the car						0.0982
						(0.567)
Number of empty seats before trip						0.137
						(0.493)
Weather						-0.501
						(0.709)
Constant	-2.363**	-3.194**	-2.796**	-2.547**	-1.965*	-2.332
	(1.037)	(1.473)	(1.199)	(1.157)	(1.159)	(1.885)
Observations	122	122	122	121	69	105

Notes: Standard errors in parentheses. The 6 columns in the table follows the same logic as table 3.4. Note that there are no omitted variables for the PMLE method.

*** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Cash-Out Proportion Analysis: Tobit

Dependent variable = percentage of the cashed-out compensation

	(1) Basic	(2) Profile	(3) Knowledge	(4) Motivation-1	(5) Motivation-2	(6) Others
Compensation level	0.216	0.122	0.262	0.118	-0.0318	0.0352
	(0.550)	(0.550)	(0.509)	(0.534)	(0.202)	(0.614)
Has participated during exp	4.706	5.047	-2.206	3.223	1.573	2.409
	(3.213)	(3.305)	(3.160)	(2.867)	(1.238)	(3.077)
Male passenger		-4.473				
		(2.849)				
Male driver		0.968				
		(2.279)				
Driver age group		0.0774				
		(1.176)				
Driver heard of service only			8.123*			
			(4.329)			
Driver knows how it works			4.659			
			(3.522)			
Declared monetary motivation				4.043		
				(3.100)		
Declared social motivation				-0.907	0.183	
				(2.356)	(0.892)	
Declared motivation on solidarity				-3.578	0.0842	
				(2.625)	(0.816)	
Days waited until cash-out					0.106	
					(0.128)	
Driver saw price on screen						1.902
						(2.678)
Number of children in the car						5.776
						(4.568)
Number of empty seats before trip						1.727
						(1.734)
Weather						0.768
						(1.875)
Constant	-1.314	0.254	-7.916	0.669	2.804*	-6.773
	(3.276)	(3.945)	(4.940)	(3.427)	(1.499)	(7.194)
Sigma	9.508	9.188	8.268	9.090	1.985	9.721
Constant	9.508**	9.188**	8.268**	9.090**	1.985**	9.721**
	(4.166)	(4.024)	(3.614)	(3.980)	(0.827)	(4.765)
Observations	122	122	122	121	69	105
Pseudo R^2	0.018	0.041	0.116	0.048	0.047	0.043

Notes: Standard errors in parentheses. The 6 columns in the table follows the same logic as Table 3.4. Tickets not claimed (perc_cashout=0) are also included in the regression. If we only regress on the claimed tickets ($n = 70$), the results do not change. We use Tobit model because data are restricted between 0 and 1, and are highly skewed - most of the observations are at the upper and lower bounds.

*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Donation Proportion Analysis: Tobit

Dependent variable = percentage of compensation donated

	(1) Basic	(2) Profile	(3) Knowledge	(4) Motivation-1	(5) Motivation-2	(6) Others
Compensation level	-0.0471	-0.138	-0.0279	-0.0129	-0.0615	0.0280
	(0.240)	(0.250)	(0.234)	(0.226)	(0.217)	(0.284)
Has participated during exp	-12.21	-12.71	-12.53	-12.57	-10.75	-12.41
	(.)	(.)	(.)	(.)	(.)	(.)
Male passenger		-0.00701				
		(0.962)				
Male driver		1.834				
		(1.455)				
Driver age group		0.251				
		(0.544)				
Driver heard of service only			-0.431			
			(1.179)			
Driver knows how it works			1.870			
			(1.382)			
Declared monetary motivation				-0.957		
				(1.399)		
Declared social motivation				0.304	0.0457	
				(1.066)	(0.949)	
Declared motivation on solidarity				-0.968	-0.170	
				(1.021)	(0.879)	
Passenger used gesture				1.926	1.793	
				(1.226)	(1.106)	
Days waited until cash-out					-0.103	
					(0.133)	
Driver saw price on screen						-1.032
						(1.236)
Number of children in the car						-12.38
						(.)
Number of empty seats before trip						0.334
						(0.761)
Weather						-1.133
						(1.196)
Constant	-3.227	-4.432	-3.429	-3.258	-1.968	-3.683
	(2.155)	(2.881)	(2.252)	(2.167)	(1.657)	(3.581)
Sigma	2.567	2.460	2.407	2.265	1.855	2.418
Constant	2.567**	2.460**	2.407**	2.265**	1.855**	2.418*
	(1.214)	(1.161)	(1.134)	(1.064)	(0.859)	(1.315)
Observations	122	122	122	121	69	105
Pseudo R^2	0.071	0.115	0.116	0.145	0.190	0.146

Notes: Standard errors in parentheses. The 6 columns in the table follows the same logic as table 3.4. Tickets not claimed perc_donation=0) are also included in the regression. If we only regress only with the claimed tickets ($n = 70$), the results do not change.

*** p<0.01, ** p<0.05, * p<0.1

CHAPTER 4

THE IMPACT OF THE SNCF STRIKE ON RIDESHARING: A NOVEL APPROACH OF CONSUMER SURPLUS ESTIMATION USING BLABLACAR.COM DATA

Timothy Yu-Cheong Yeung[1] and Dianzhuo Zhu[2]

Abstract[3]

We estimate the impact of the strike of the French railway monopoly (SNCF) on ridesharing usage and user welfare. From April to June 2018, railway workers went on strike every two out of five days. We collect daily trip level data from the public API of BlaBlaCar, the largest inter-city ridesharing platform in France. Our data covers the entire strike period and one month afterwards of 78 representative routes in France. Our results show that on an average strike day, demand increases by 29 percent while supply increases by 7 percent. We then use a novel method to estimate the price elasticity of the demand and consumer surplus of each route per day. Different from traditional methods that rely on equilibrium analysis, we exploit the transaction-level data to construct the market supply curve and the observed transaction curve, from which a true market demand curve and a consumer surplus are conservatively estimated. We further use propensity score matching to impute the consumer surplus estimate of an additional 318 routes that have not been included in the initial data collection to give a more comprehensive evaluation for the whole of France. On an average non-strike day, BlaBlaCar generates 79,413 € of consumer surplus, while an average strike day generates 97,166 €, an increase of 17,753 €. Our work suggests that inter-city ridesharing contributes substantially to the social welfare, serves as a flexible substitute for the railway service and ridesharing should be integrated into the design and management of the transportation network.

Keywords: Digital platforms, Railway strike, Consumer surplus, Demand estimation

JEL codes: R41, D16, D69

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4.1 Introduction

The International Labour Organization (ILO) recognizes that strike action is a fundamental right of workers. Debates are still ongoing whether public service workers are entitled to this right. According to the ILO, public transportation is not an essential public service. Thus, its workers should be entitled to the right to strike. Since public transportation often occupies a significant role in facilitating the normal functioning of an economy, the stakes are high that its labor unions are usually powerful.

An example would be the strike of the French national railway company (*Sociéte Nationale des Chemins de Fer* in French, abbreviated as SNCF) from April to June 2018, one of the most severe strikes in the history of the transportation sector in France. During the three months, a nationwide strike was organized every two out of five days, forcing millions of passengers across the nation to search for alternatives. An option is ridesharing. Digital ridesharing platforms that match passengers and drivers online have become popular in recent years. In France, the long-distance ridesharing sector, which is a close substitute for the railway, is led by BlaBlaCar, a French unicorn company. Since these platforms do not own cars themselves and rely on the participation of the users, they are very flexible in adjusting supply capacity, which is advantageous during a demand shock such as the SNCF strike. This paper investigates this substitution relationship and estimates the impact of the SNCF strike on the supply and demand of ridesharing, and verifies if and how much economic value is created by BlaBlaCar during the strike period which helps to recover the welfare loss due to the strike.

Digital platforms have opened up avenues of research since their data are relatively more available and abundant. Through the BlaBlaCar's official API (Application Programming Interface), we obtain information on almost all posted trips (supply) and bookings (demand) during the strike period of 82 major routes. This work utilizes the data collected from the API to construct the market supply curve and proposes a novel method to estimate the price elasticity of demand, and thus the market demand curve. The construction of the market supply curve is then relatively straightforward. As we know the number of seats each driver proposes, as well as the price of each seat, we can then aggregate the individual supply curves horizontally to construct the total market supply of seats at each price.

The construction of the market demand curve is more complicated than the supply curve because we do not observe consumers' maximum willingness to pay. Aiming to utilize transaction-level data, we first construct an "observed" market demand curve by assuming that the passenger's maximum willingness to pay coincides with the price paid. This observed market demand can be considered as the lower bound of the true market demand curve, since a passenger may well accept a higher price than was paid. The area under the observed market demand curve is exactly the total payment of all transactions combined. Next, we estimate the price elasticity of the demand for the observed demand curve, using a representative range of prices, and assume that the actual market demand shares the same price elasticity. Finally, we vertically adjust the estimated market demand curve upward until the smallest consumer surplus estimate of all day-routes is non-negative and thus produce a conservative estimate of consumer surplus generated by BlaBlaCar.

In brief, we find that the strike causes the market supply to rise by 7 percent at each price level. Meanwhile, the strike leads to, on average, an increase in the number of transactions by roughly 30 percent at each price level. The result confirms our expectation that the ridesharing supply is less elastic than the demand because there is a higher barrier to become a driver than to become a passenger. By comparing the estimated market demand curves on strike and non-strike days, we conclude that the strike leads to an average increase in consumer surplus generated on BlaBlaCar by 21%.

To deliver a more general message for the whole of France, we include other routes involving smaller cities and assign consumer surplus estimates to them by propensity score matching. Thus, BlaBlaCar, on an average non-strike day, generates 79,413 €, 17,752 € in addition to an average strike day.

The rest of this paper is organized as follows. Section 4.2 is a brief literature review on the substitution of transportation modes during disruptions and the welfare implications of digital transportation platforms. Section 4.3 gives some background information about the SNCF strike and BlaBlaCar. Section 4.4 presents the data collection and cleaning process, as well as some summary statistics. Sections 4.5 and 4.6 demonstrate the method we use to construct the market supply curve and the observed demand curve, and show the impact of the strike on supply and demand. Section 4.7 estimates the true market demand curve and computes a consumer surplus estimate generated by BlaBlaCar during the strike. Section 4.8 extends our results to unincluded routes in the first round by propensity score matching. Section 4.9 compares the individual costs of a passenger's different choices, and the social welfare of ridesharing and taking the railway by considering social and environmental costs. The last section discusses the importance of our results and draws the paper to a conclusion.

4.2 Literature Review

Transportation network disruptions often occur and have substantial impacts on the routine and well-being of commuters. Works on the impacts of transportation interruptions are mainly city-level case studies, which are limited in terms of the generalization of their results to larger areas (S. Zhu & Levinson, 2012). Strikes in a public transportation system is a major category of transportation disruptions that forces people to change their commuting behavior. Exel and Rietveld (2001) studied 13 public transportation sector strikes and found that, on average, only 10-20% of passengers canceled their trips while others actively sought alternatives. People may eventually continue with the alternative and form a new habit. A recent paper by Larcom, Rauch, and Willems (2017) found that the London underground strike in 2014 led to lasting changes in commuters' daily routines. As they were obliged to discover alternatives, some learned that the new commuting routes are more efficient or pleasant than the original ones. Instead of searching for alternatives within the same transportation mode, an inter-modal switch was also quite common (see Fearnley et al. (2018) for a review of inter-modal elasticities), with carpooling or ridesharing as an outside option. Exel and Rietveld (2001) showed that the switch to carpooling is indeed a short-term solution, whether it is organized by the local authorities as a policy tool or spontaneously among acquaintances and employees.

The rise of digital ridesharing and riderailing platforms may now serve as a more effective substitute during strikes and other transportation disruptions, as they can match a large number of strangers, and they are flexible in adjusting supplies to meet demands. Previous research has focused on the general features and pricing strategies of traditional two-sided platforms but not on the sharing platforms (Bolt & Tieman, 2008; Hagiu & Wright, 2015; Rochet & Tirole, 2006). Due to constraints on data confidentiality and availability, current research on these latter platforms tends to focus on Uber data in the American market. Topics include drivers' working behavior under price surges (M. K. Chen, 2016), gender pay gaps (Cook et al., 2018), racial and gender discrimination (Ge et al., 2016) and others. Some papers attempt to measure the welfare impact of Uber. On the passenger side, P. Cohen et al. (2016) exploited Uber's price surge discontinuities to estimate the passenger price elasticity of demand at various points of the demand curve to estimate its consumer surplus. On the driver side, M. K. Chen, Rossi, Chevalier, and Oehlsen (2019) shows that Uber's flexible working schedule allows drivers to earn twice as much surplus as in non-flexible situations. Kim et al. (2018) compares Uber with taxi services in New York City and argued that Uber's entry is welfare-enhancing since passengers in broader areas of NYC now have access to taxi or Uber services. Lam and Liu (2017) also uses Uber and Lyft data from their API as well as taxi data in NYC to estimate the demand and consumer surplus, with a focus on the calculation of surplus caused by shorter waiting times. In other research using UberPool data in Chicago, Schwieterman and Smith (2018) finds a 67.6% time reduction using UberPool between neighborhoods and a US$0.38 per minute saving compared to public transit. Various evidence suggests that Uber, as a digital platform with flexible on-demand inner-city transportation supply, is welfare enhancing. It increases ridership as an alternative option of the current public transportation system (Hall et al., 2018).

As the largest inter-city ridesharing platform in Europe, BlaBlaCar has been mentioned in some papers aimed at discussing the sharing economy in general. Research dedicated to BlaBlaCar is rare, though recently is drawing more and more attention by scholars and the public. Shaheen et al. (2017) investigates the characteristics of passengers and drivers on BlaBlaCar by conducting surveys. Farajallah et al. (2019) web scrapes data on BlaBlaCar and finds that more experienced drivers tended to set lower prices but sell more seats. To the best of our knowledge, no economics research has yet been carried out to estimate quantitatively the welfare impact brought by the ridesharing platform.

The welfare impact of digital ridesharing platforms is even more relevant during transportation disruptions, as they could recover welfare losses. Since SNCF is a state-owned monopoly and occupies the majority of the market of long-distance public transportation (Crozet & Guihéry, 2018), the strike causes large-scale welfare loss and forces people to look for other remedies. Studying users' behavior on ridesharing platforms supplements our understanding of the impact caused by a disruption of public transportation, the margins for negotiations held by SNCF and the labor unions, and, more generally, the role of digital sharing platforms in the transportation sector.

Our paper fills empirical and methodological gaps in several aspects. Firstly, it provides quantitative evidence on the behavioral changes and welfare impact of a severe transportation disruption –the SNCF national strike in 2018 – by using comprehensive data extracted from the API of BlaBlaCar. Secondly, the scope is not limited to a single city but covers the whole of France due to the nationwide presence of BlaBlaCar. Thirdly, while the current research focuses on short-distance driver-passenger matching platforms, our work studies an online matching platform that competes with long-distance transportation modes. Fourthly, it measures the extent of the substitution between ridesharing organized by a digital sharing platform and public transportation. Finally, it proposes a novel approach to estimate the price elasticity of demand and also the consumer surplus using transaction-level data.

4.3 Background Information

4.3.1 SNCF Strike and the Opportunity for Ridesharing

In late March 2018, the railway workers of SNCF (the French national railway company) decided to start an unprecedented strike, which began on 3rd April and ended on 28th June. The labor union initiated the strike in order to oppose the French government's reform plan of SNCF. The plan includes abolishing the "railway worker" status that brings many advantages compared to other sectors, privatizing the railway sector in favor of competition, closing some unprofitable regional train lines, and enforcing that SNCF itself, instead of the state, pay its debts. For those railway workers, abolishing their status would be the most disadvantageous reform. This status was created in the early 20th century to compensate for the difficult working conditions of railway workers at that time. The bonuses of this status includes a lifelong job guarantee, more holidays than average workers, a higher retirement pension, lower house rent, free train tickets for themselves and close relatives such as parents, grandparents, children, and partners.

One distinctive feature of this strike is the schedule, which was published in mid-March. The labor union decided to go on strike every two out of five days from April to June, even if the scheduled strike days coincided with weekends or national holidays when the demand for travel surges.[4] Since the strike days were announced well before, people could anticipate the inconvenience caused and make other plans if possible. Intuitively, the later the dates are, the more time people would have to adjust their travel plans, and the less negative the impact would be. However, the exact train schedules remained uncertain until the morning of the strike day.

The strike became breaking news in the subsequent weeks and impacted almost every resident in France. Competitors in the transportation sector found their opportunities to propose solutions and to capture an uncatered market. The ridesharing sector was a direct beneficiary. The Parisian regional transportation authority (Île-de-France Mobilités) even formed a partnership with eight inner-city ridesharing platforms, including one platform owned by SNCF (IDVROOM), and set all ridesharing trips inside Île-de-France to be free of charge on strike days. For inter-city trips, where the impact was expected to be severe, BlaBlaCar, the most popular long-distance ridesharing platform in France, would be the natural substitute for many passengers.

4.3.2 Introduction of BlaBlaCar

BlaBlaCar is the largest inter-city ridesharing platform in Europe. It was created by Vincent Caron in 2004 and was initially called Covoiturage.fr. Frédéric Mazzella then bought the domain in 2006, who eventually changed the name into BlaBlaCar.fr in 2013. As of March 2019, besides France, BlaBlaCar operates in 21 other countries, which are all in Europe, except for Mexico, Brazil, and India.

The business model of BlaBlaCar relies on its online platform. Passengers can launch a search

[4] Appendix C.1 shows the calendar of strike dates in April, May, and June.

by entering a departure city, a destination city, and a departure date. The platform then shows all the qualified and available trips that drivers have proposed, ranked by an algorithm that takes into account the driver experience, departure time, available seats, price, departure and destination location matching, among others.[5] Passengers can view a snapshot of some of the proposed rides, and then decide which one to check for more information and booking. They could also click on a driver's profile and learn more about the driver's personal preferences, ratings, and ID verification. Appendix C.2 shows the process of a search as of February 2018.[6]

Drivers can not actively search for passengers on the platform, and BlaBlaCar does not propose automatic matching like Uber. Drivers are mainly passive and could only wait for requests from passengers. However, BlaBlaCar drivers have the discretion to set prices. When a driver arrives at the price setting stage, the system will propose a default reference price, but she can still choose a higher or a lower price within a range of prices, where the platform regulates the upper and lower limits.[7] The final price that the passengers see is the price set by drivers plus the commission to BlaBlaCar. Commission levels increase incrementally as the price set by the driver increases.[8]

4.4 Data

4.4.1 Data sources

Our dataset combines three data sources: BlaBlaCar's API, BlaBlaCar's website, and SNCF's press documents. All information collected is publicly available. BlaBlaCar's open API supplies the majority of the dataset.[9] However, BlaBlaCar's API will only keep historical data for a limited period, so that the data we have for this paper can no longer be retrieved from the API, and its terms of use do not allow us to disseminate the data that is no longer available in the API. It contains almost all the information about a trip, which could also be seen by everyone, no matter if they have registered with the platform or not. Important variables are the departure and arrival cities, departure date and time, price proposed by the driver, commission level, price seen by the passenger, total seats offered and booked. No personal

[5] Trips are ranked first by their departure time, from the closest to the present time to the furthest away. However, among the trips departing at the same time, there is no single rule of ranking. The algorithm takes into account all the factors, and we do not know how exactly it works.

[6] BlaBlaCar has changed the trip search and trip information layouts after our data collection period. We put the historical version during the data collection period in the Appendix to keep the paper coherent.

[7] Appendix C.3 shows the way we collect the reference price information.

[8] Appendix C.4 shows how the commission levels are decided.

[9] https://dev.BlaBlaCar.com/

information such as the driver's name or age is available on the API, even though such (self-reported) information is publicly available on the page of the trip. In this paper, we treat the drivers as exchangeable, meaning that the individual drivers' profiles are not considered in the welfare analysis.

4.4.2 API Data Collection and Route Selection

The data collection from the BlaBlaCar API starts on April 1, 2018, two weeks after SNCF's announcement of the strike and two days before the beginning of the strike (April 3). It ends on August 3, 2018. We extend the collection period one month after the end of the strike to use the post-strike month as the control period.[10] From 1st April to 3rd August, we run the data collection program every day at the end of the day, typically from 18:00 to 19:00. The choice of a daily retrieval is a trade-off between accuracy and convenience.

We limit our daily data collection to a reasonable scope, not only because of the API daily query limit but also it is nearly impossible to exhaust all trips on the website.[11] We select 82 routes (41 pairs of cities) that are the most representative and which we believe to be more likely affected by the strike. These routes included main French cities (and their suburban areas) and some second-tier cities (and their suburban areas).[12]

We also take into consideration the balance of the geographic representation so that each part of France has some sampled cities, as shown in Figure 4.1. We also pay attention not to include two routes that overlap in order to avoid double counting. Routes can be divided into three categories. The first one is between two major cities. We select seven cities as the main cities: Paris, Lyon, Marseille, Bordeaux, Toulouse, Nantes, Strasbourg, balancing the size of the city, and the geographic representation. The second category is between a major city to a nearby second-tier city. An example is Paris-Reims. The third category is between two second-tier cities that are close to each other. We do not include trips of two cities that are far from each other. For example, the trips from Lille to Paris and from Paris to Lyon are included, but not from Lille to Lyon, even though Lille and Lyon are both on the list. A driver who travels from the northern city of Lille to the south-eastern city of Lyon will almost surely pass by Paris.

[10] Appendix C.5 details the protocol of data collection and cleaning.

[11] The way of retrieving the data via the API is by sending queries that contain selection criteria. We can set selection criteria on various variables such as the departure and arrival cities, and the date of departure. By setting the departure and arrival cities (at least one of them is required), we are restricting ourselves to a subset of the complete data. Also, as we are not retrieving data continuously, there may be some trips that have appeared but then disappeared in between two collection sessions.

[12] In 2018, the ten largest cities (including their suburban areas) in France are Paris, Lyon, Marseille-Aix-en-Provence, Toulouse, Bordeaux, Lille, Nice, Nantes, Strasbourg, and Rennes. They are all included in our data sample.

She may well add a stop in Paris, which will make the trip appear both in the Lille-Paris and Paris-Lyon requests. If we also include Lille-Lyon in the protocol, the trip may be included twice. Since BlaBlaCar asks drivers to set a price for each subsection of the entire trip, we can well treat Lille-Paris-Lyon as two independent routes. Appendix C.6 lists the 41 pairs of cities and the categories to which they belong.

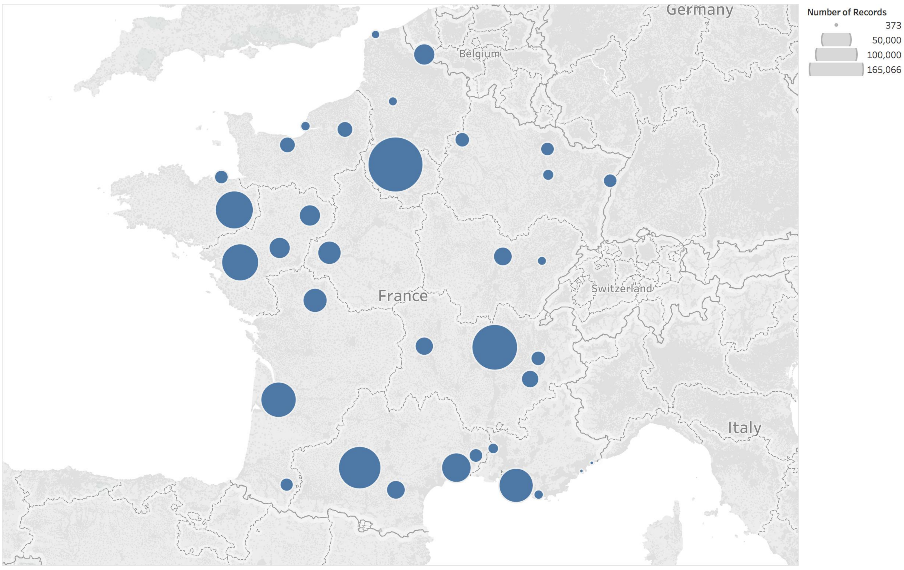


Figure 4.1: Spatial Distribution of Selected Arrival Cities

The graph shows the spatial distribution of the arrival cities. The larger the size of the circle, the more trips arrive at that destination. Paris is the most popular destination, followed by Lyon and Toulouse. Note that the graph only uses the data of the selected 82 routes, in which some cities appear frequently and in multiple routes. Although the routes in our sample are believed to be the most frequented routes, the graph using the complete data is certainly different from the one we show. The same caveat applies to the other graphs and data analysis.

4.4.3 Supplementary Information from BlaBlaCar.fr and SNCF Press Releases

Apart from trip information available from the API, we augmented our dataset with supplementary information from the BlaBlaCar website and SNCF press releases. Even though drivers can propose the price themselves, they do not enjoy full liberty in doing so. BlaBlaCar sets a default price level, and the upper and lower price limits. These price levels are correlated with the length of the route in order to maintain the principle of cost-sharing, neither to encourage users to become professional profit-making drivers nor to discourage them with too fierce price competition among drivers.[13] We collect the default,

[13] If a driver wishes to raise the price up from the default level, then she will receive an alert that most of the other trips are cheaper than what she charges and that staying with the default price would maximize the chance of being booked. If she still wishes to increase the price level, the color of the price switches from green to orange and eventually to red. On the other hand, setting the price lower than the default level does not trigger any warning message or change of color. On the mobile application, the color of the price never changes, but the drivers receive a warning message. Deviating from the default price level is even more complicated on a mobile device because drivers need to confirm twice to adjust the price up or down. See Appendix C.3 for a visual demonstration. These obstacles may also explain why most of the drivers set the price at the default level or very close to it.

highest, and lowest price levels of each selected route by simulating the driver's trip publication process on the website with a registered driver account.[14] These regulated price levels do not change within the routes during the data collection period.

The final piece of information is the strike participation rate announced by SNCF. On most strike days, SNCF publish a press release with an overall strike participation rate.[15] We collect all the available strike participation rates and fill in the missing values by computing the average strike participation rate using information before and after the concerned date. For non-strike dates, the strike participation rate is zero. We also create indicator variables for strike days versus non-strike days, weekdays versus weekends, and whether a coach company proposes this trip (since BlaBlaCar starts to collaborate with a coach company during the data collection period). For three experimental round routes, passengers could find coach offers listed together with individual ridesharing offers. We exclude these routes from our analysis.

4.4.4 Data Cleaning and De-biasing

At the end of the data collection period, we have an unbalanced panel dataset of trips departing from April to July 2018, which belong to the pre-selected 82 routes. A trip may show up several times as it may be posted within the 15 days before its departure date, but the dataset is nevertheless unbalanced. Being able to trace back up to 15 days of a trip allows us to observe the evolution of bookings. Changes in the supply side such as the price level and total number of proposed seats can also be traced.[16] Most trips have no changes for several days or the entire 15 days. For our analysis, we need only to keep the final observation of each trip, but we create additional variables to indicate changes. To ensure that our analysis is robust, we have to deal with two biases in the records. First, the last observations may not be accurate as some records may have been deleted before we were able to capture the last status. Second, drivers may post multiple trips on the same day and cancel some or all trips.[17]

[14] See Appendix C.3 for a demonstration.

[15] The information is extracted from this link regularly during the strike period: https://www.sncf.com/fr/groupe-sncf/newsroom/communique-de-presse.

[16] Before booking occurs, drivers are free to modify any information of the trip, including but not limited to the price level, available seat number, trip description, and correspondence cities. Once a booking is made, drivers can no longer modify the price unless the passenger cancels a booked seat. See https://www.BlaBlaCar.fr/faq/question/comment-modifier-mon-annonce-avant-et-apres-une-reservation for more information on trip modification.

[17] Appendix C.5 shows further details cleaning and de-biasing of the data.

4.4.5 Summary Statistics

Our dataset contains (almost) all of the information for the trips of the 82 selected routes from 1st April to 31st July 2018. In total, we have 1,022,160 trip offers, of which 499,674 trips have at least one booking. The rate of unbooked and cancelled trips is 51%.

As illustrated in Figure 4.1, we cover all the major cities in France and some second-tier and even smaller cities. The cities are geographically distributed in a balanced way. Paris is no doubt, the most popular destination, followed by Lyon and Toulouse. Figure 4.2 shows the total number of offers (count of single vehicles) per route from 1st April to 31st July 2018. The busiest route is Nantes-Rennes, reaching almost 32,000 trips (one-way) in the four months since the two cities are dynamic and geographically close (1.5 hours by car). The second and third most popular routes, Montpellier-Toulouse and Bordeaux-Toulouse (2.5 hours by car), share the same dynamism and proximity as Nantes-Rennes. The least popular route is Cannes-Nice, two closely-located tourism cities. For all routes combined, the average number of vehicles offered per route is 12,465 during the period, with a total of number of 1,825,988 seats offered. For Nantes-Rennes, 57,690 seats are offered, while only 373 seats for Cannes-Nice. As shown in Table 4.1, on average, all routes combined, a strike day has 16,388 seats offered, 14% more than a non-strike day, which has 14,376 seats offered.

Figure 4.3 illustrates the evolution of the daily seat supply. We take a representative route, Paris-Lyon, as an example. Again, the strike days are marked in blue and non-strike days in orange. Visually, the strike seems to induce more offers, but the fact of departing on weekends seems to be even more salient. We also observe that starting from mid-May, the number of trips offered begins to decline. The busiest day of this route is 4th May, with 593 vehicles offered.

On the demand side, the strike seems to have a more considerable impact compared to the supply side. Also, from Table 4.1, on average, for all routes combined, a strike day has 7,130 seats booked, 23.5% more than a non-strike day, which has 5,775 seats booked. The overall average number of passengers per booked vehicle is 1.5. In terms of booking habits, Figure 4.4 documents the timing of the first booking of a trip. The majority of the first bookings take place within two days of departure.

4.5 Effects of the Strike on Ridesharing Supply

One of the main advantages of the dataset is that we observe detailed supply and demand information at the transaction level. While most of the datasets found in the literature only observe realized transactions,

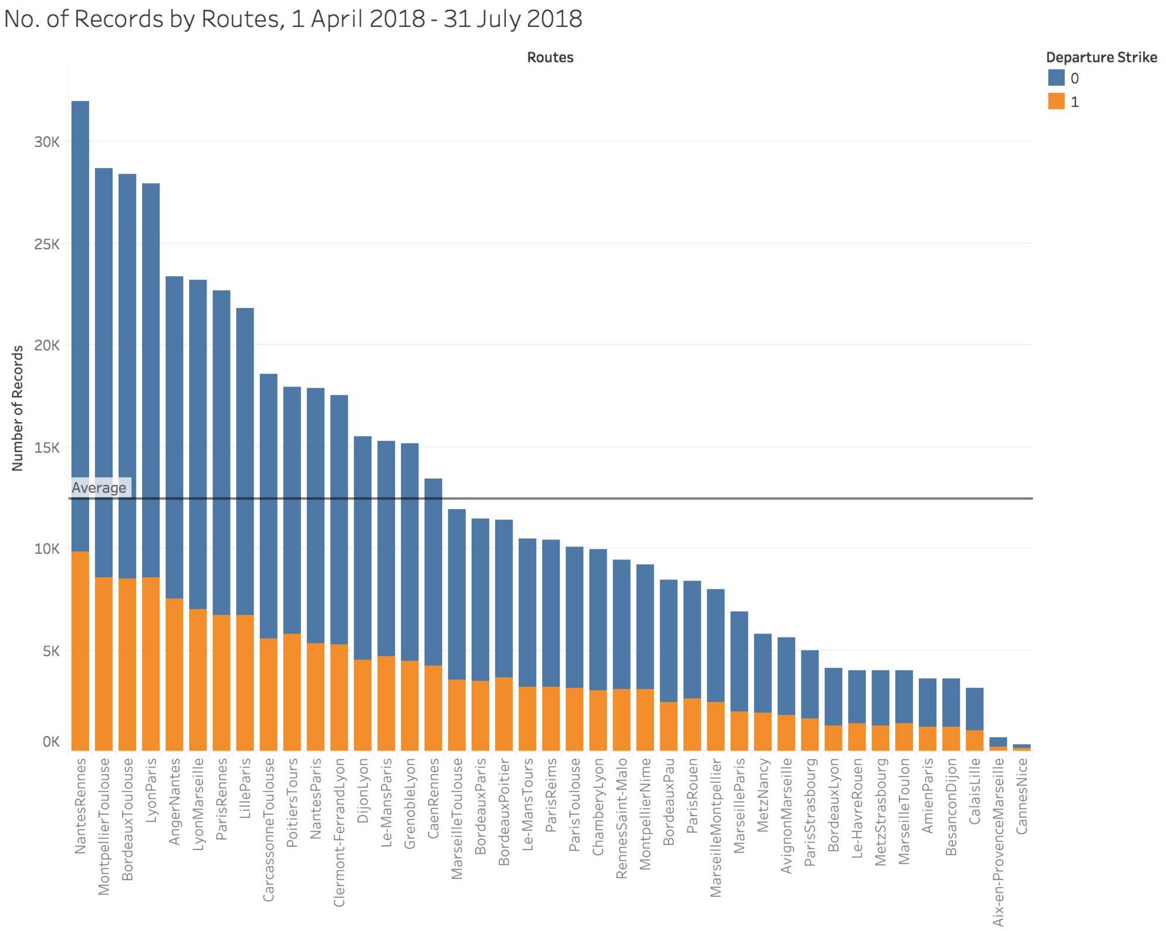


Figure 4.2: Route Popularity Ranking by Trip Offer for the Scraped Sample

Route popularity ranking according to total trip offer from 1st April to 31st July, with strike days in orange and non-strike days in blue. We only display the 41 one-way routes.

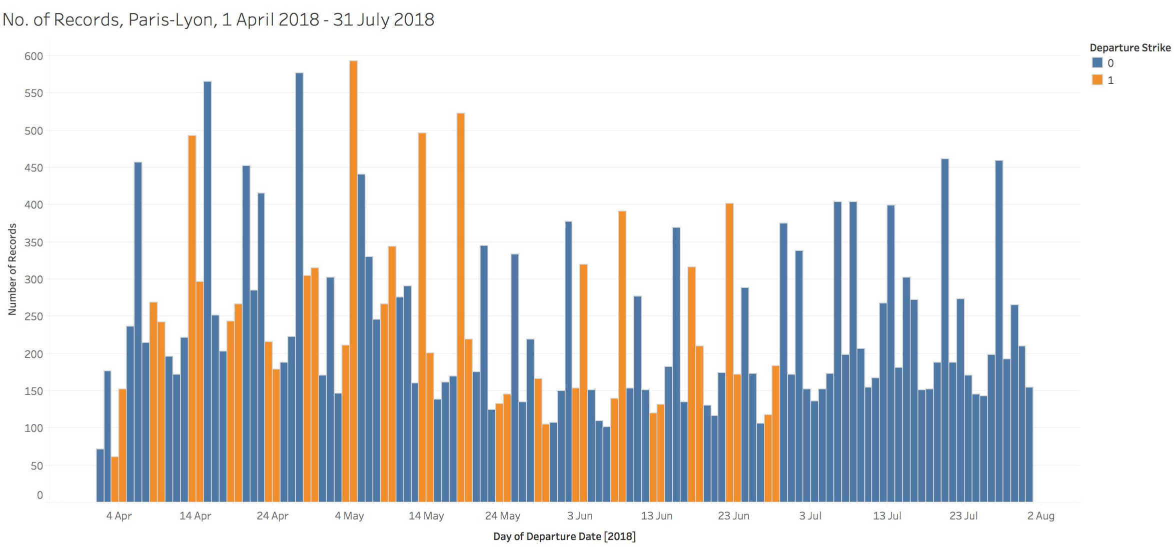


Figure 4.3: Daily trip offer of Paris-Lyon, 1st April to 31st July (Orange: Strike Days, Blue: Non-Strike Days

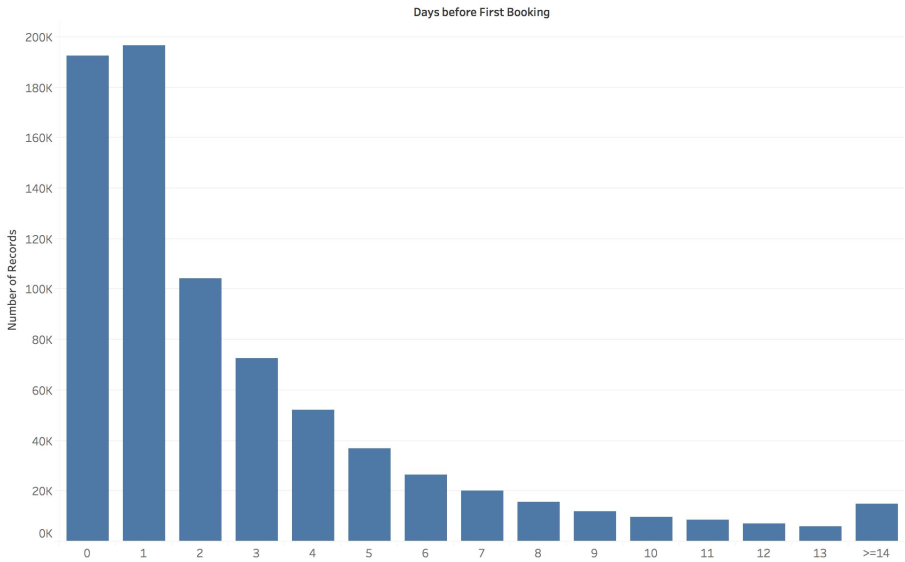


Figure 4.4: Timing of First Booking Measured by Days Before Departure

Table 4.1: Number of Seats Offered and Booked per Day: Non-strike vs. Strike

	Mean	SD	Min	Max
Total Seats Offered				
Non-Strike	14,376	5,818	3,923	29,744
Strike	16,388	7,050	8,493	35,222
Total Seats Booked				
Non-Strike	5,775	2,443	1,616	12,214
Strike	7,130	3,172	3,575	15,567

we observe the number of seats each driver offers to the market together with the price information. Each observation thus reveals a driver's willingness to supply. However, we do not observe the willingness to supply over a range of prices. To complete the construction of an individual supply curve, we assume that drivers are willing to offer the same number of seats at any prices higher than the quoted price, but will offer no seats at lower prices. During a short period, an individual can only offer a fixed number of seats, so the individual supply curve is perfectly inelastic over a range of prices. If we assume that drivers have no external option (i.e. no opportunity cost) and that they must carry out their travels, an individual supply curve is a vertical line starting from the price set by the driver up to infinity, as shown in Figure 4.5.

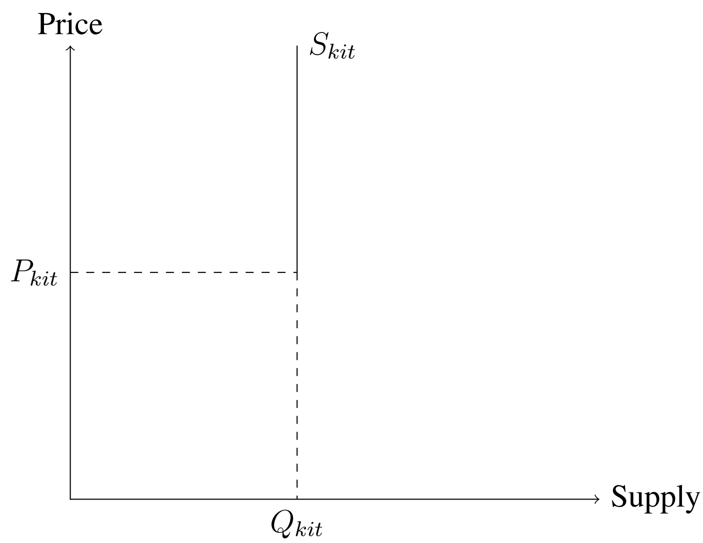


Figure 4.5: Illustration of An Individual Supply Curve

An individual driver k with Q_{kit} empty seats on route i on day t who sets the price per seat at P_{kit} would accept at any price equal or higher than P_{kit}, but would refuse at any price lower than P_{kit}. In the short term, these quantities are invariant, which makes the individual supply curve S_{kit} perfectly inelastic.

The market aggregate supply is the horizontal summation of individual supply curves, as illustrated in a simplified way in Figure 4.6. We add up all the individual supply curves for each route daily and obtain a panel dataset of the market supply of each route for the four months. Although supplies of the same route on the same day are heterogeneous in terms of the driver profile/quality, departure place and time, among others, we decide to maintain our aggregation level at the calendar day.

Figure 4.7 shows an example of the observed aggregated supply curve of the route Paris-Lyon. There is a spike of supply at the reference price, which is set as the default price shown to drivers. In this case, the default price is 30 €. We can reasonably assume that some drivers quoting 30 € would have proposed

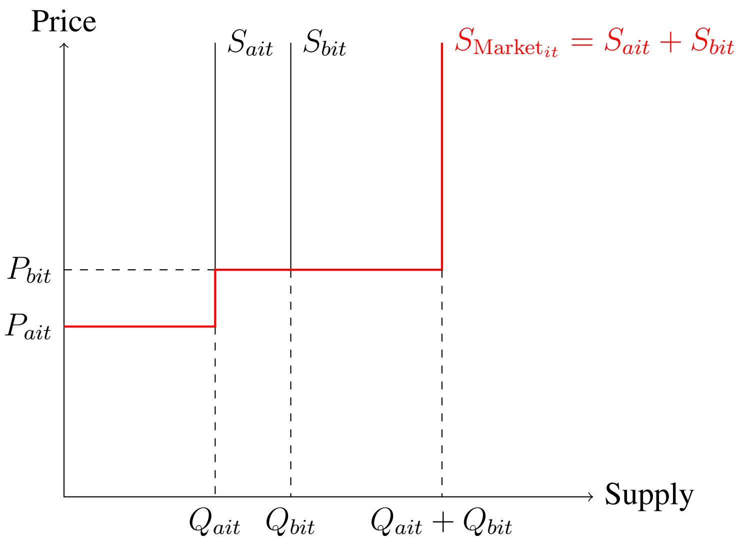


Figure 4.6: Simplified Illustration of Horizontal Summation of Individual Supply Curves to Form the Market Supply Curve.

There are only two individuals in the market, A and B. They offer Q_{ait} and Q_{bit} seats respectively for route i on day t at P_{ait} and P_{bit}. The black solid lines S_{ait} and S_{bit} represent individual supply curves of driver A and B of route i in day t. The red solid line $S_{\text{Market}_{it}}$ represents the aggregated market supply curve of route i in day t. When the price is below P_{ait}, nobody is willing to supply. Between P_{ait} and P_{bit}, only individual A is willing to supply and thus the market supply curve is the same as the individual supply curve of individual A. Beyond P_{ait}, the market supply is horizontally extended to $Q_{ait} + Q_{bit}$.

and accepted a price lower than 30 € had it not been shown as default.[18]

Our next step is to estimate the impact of the SNCF strike on the supply quantitatively. Figure 4.7 implies that the relationship between price and supply is cubic. The cubic relationship remains, though it is less obvious, after taking the logarithms of the price and supply. More precisely, we estimate the following model:

$$\ln Q_{it}^s = \alpha^s + \beta_1^s(\ln P_{it}) + \beta_2^s(\ln P_{it})^2 + \beta_3^s(\ln P_{it})^3 + \beta_4^s\text{Strike}_t + \boldsymbol{x}'\boldsymbol{\gamma}^s + \epsilon_{it}^s \tag{4.1}$$

where Q_{it}^s is the supply of route i on day t, P_{it} is the price proposed by drivers on route i on day t, Strike_t is an indicator variable that takes value one if day t is a scheduled strike day, the vector $\boldsymbol{x}$ includes control variables such as the route, month, weekday, and national holiday fixed effects, and the error term ϵ_{it}^s is assumed to be randomly distributed with mean zero.

Results are shown in Table 4.2. Column (1) reports the estimates of the coefficients of Equation 4.1. The coefficient of the strike day indicator is positive and significant. On average, a strike day leads to a 7

[18] Although drivers are free to deviate from the default price level and set their price as long as it is within the range of the price limits, having a default option still heavily influences their choices. We observe the same pattern among all supply curves.

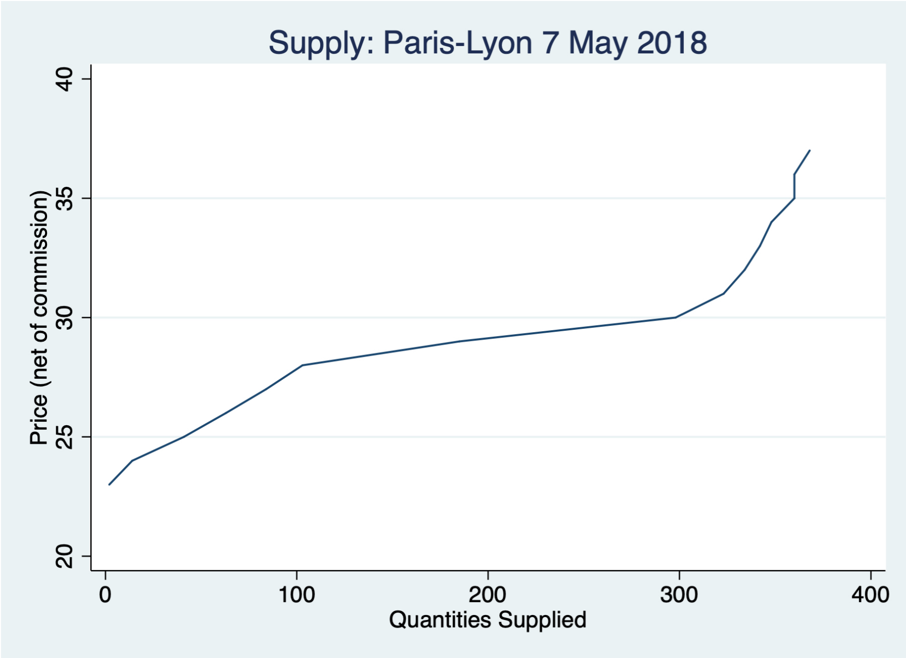


Figure 4.7: Illustration of A Typical Market Supply Curve for the Paris-Lyon Route on 7 May 2018.

percent increase in supply compared with a non-strike day. In Column (2), are the coefficient estimates when we add an interaction between routes and the squared price levels, as well as an interaction between routes and the cubic price levels, since each route has its own price limits. The magnitude of the effect of strike falls to 6.7 percent. For Column (3), we replace the strike day indicator by the overall strike staff participation rate published by SNCF while keeping all controls and all interaction terms added in Column (2). An increase in the strike participation rate by one percentage point correlates with a 0.34 percent increase in supply. As the average strike participation rate during the strike period is approximately 20 percent, supply increased by 6.8 percent on an average strike day, which is consistent with Columns (1) and (2).

There are at least two possible explanations of the increase in supply. Firstly, SNCF passengers affected by the strike may decide to drive themselves and offer their empty seats on BlaBlaCar. Secondly, some drivers' willingness to supply increases because they want to take advantage of the strike to make extra money. The impact of the strike on supply is nevertheless relatively small compared to the impact on demand, as we shall see in the next section.

Table 4.2: Effect of Strike on BlaBlaCar Supplied Seats (Change in Percentage)

	(1)	(2)	(3)
$\ln P_{\text{driver}}$	-0.2415	-17.6506***	-17.6752***
	(0.7499)	(0.0336)	(0.0319)
$(\ln P_{\text{driver}})^2$	2.4456***	41.7960***	41.8615***
	(0.3119)	(0.0767)	(0.0723)
$(\ln P_{\text{driver}})^3$	-0.2755***	-22.8149***	-22.8535***
	(0.0400)	(0.0438)	(0.0412)
Strike Day	0.0709***	0.0665***	
	(0.0094)	(0.0098)	
Strike Participation Rate			0.3420***
			(0.0503)
Route×Price	No	Yes	Yes
Linear Time Trend	Yes	Yes	Yes
Route FE	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
N	73249	73249	73249
R^2	0.815	0.890	0.890
No. of Routes	82	82	82

Standard errors are in parentheses and are clustered by Routes

* $p < .1$, ** $p < .05$, *** $p < .01$

4.6 Effects of Strike on Observed Ridesharing Demand

The construction of the market demand curve is less straightforward than that of the market supply curve for two reasons. Firstly, we only observe the transactions and not the maximum willingness to pay. It is unlikely that passengers always transact at their highest acceptable price. We first construct the observed demand curve using prices that the passengers paid. The true demand curve must lie above the observed demand curve because the passengers' maximum willingness to pay is very likely to be more than the price they paid. Secondly, we cannot observe the passengers whose maximum willingness to pay is below the lowest price limit since there is no offer. The true demand curve should extend until the price reaches zero, while the observed demand curve stops at the actual quantity transacted. This second issue is not critical for us because the consumer surplus is computed based on the number of actual transactions.

The construction follows the same logic as that of the market supply curve. Any individual has a unit demand, and she will accept all the prices below the maximum price. Moreover, no individual needs to transport more than one person. Thus, the individual demand curve is a straight line up until the price one paid, and the aggregated observed demand curve is the horizontal sum of the individual observed demand curves. It must be decreasing. As for the market supply curve, we aggregate the demand for each route per day. Figure 4.8 shows an example of the daily observed demand curve of a typical route, Paris-Lyon.

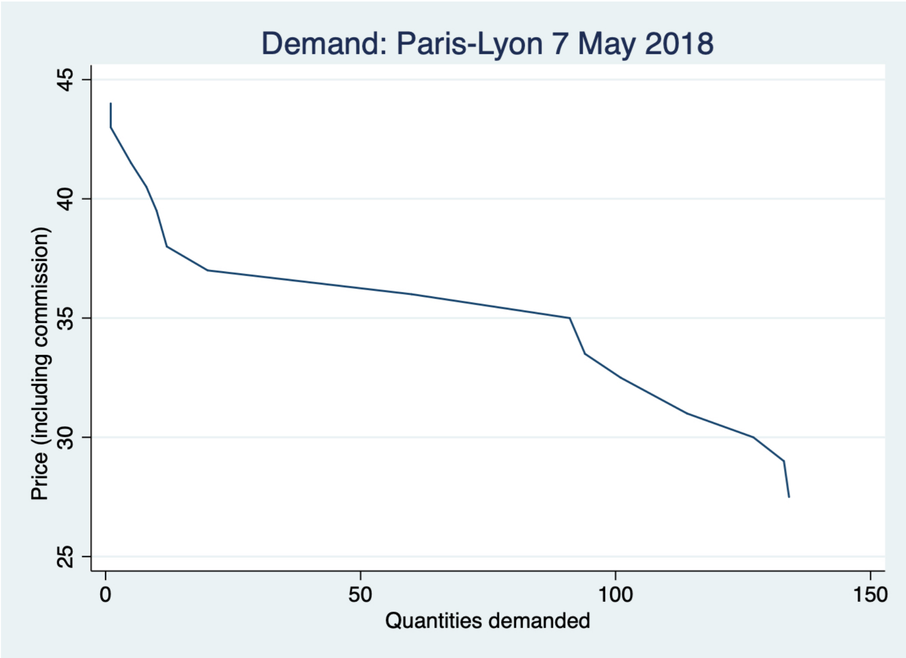


Figure 4.8: Illustration of a Representative Observed Demand Curve Using the Paris-Lyon Route on 7 May 2018.

We are interested in the impact of the strike on the observed market demand. Figure 4.8 indicates that the relationship between price and demand is also cubic. We thus estimate the following equation:

$$\begin{aligned}\ln Q_{it} = \alpha + \beta_1(\ln(P_{it} + \mathrm{Com}_i)) + \beta_2\big(\ln(P_{it} + \mathrm{Com}_i)\big)^2 + \beta_3\big(\ln(P_{it} + \mathrm{Com}_i)\big)^3 \\ + \beta_4 \mathrm{Strike}_t + \boldsymbol{x}'\boldsymbol{\gamma} + \epsilon_{it} \end{aligned} \tag{4.2}$$

where Q_{it} is the demand (transacted) of route i on day t, $P_{it} + \mathrm{Com}_i$ is the price paid by passengers of route i on day t including the commission to BlaBlaCar. The other variables remain the same as in Equation 4.1. The results are shown in Table 4.3. Column (1) reports the estimates of the coefficients. On average, the observed market demand increases by 28.9 percent on a strike day. Column (2) are the coefficient estimates when we add an interaction between routes and the squared price levels, as well as an interaction between routes and the cubic price levels. The impact magnitude is almost the same, while the R-squared improves. For Column (3), we replace the strike day indicator by the overall strike participation rate. The average strike participation rate during the strike period is approximately 20 percent, which implies that on an average strike day, the observed market demand increases by roughly 29.5 percent, which is also in line with columns (1) and (2). Compared to the supply, which increased by 7 percent during the strike, the demand is four times more elastic.

Table 4.3: Effect of Strike on BlaBlaCar Booked Seats (Change in Percentage)

	(1)	(2)	(3)
$\ln P_{\text{passenger}}$	2.7132***	-37.7277***	-37.5931***
	(0.9415)	(0.1702)	(0.1677)
$(\ln P_{\text{passenger}})^2$	-1.8028***	37.7031***	37.6166***
	(0.3839)	(0.1636)	(0.1615)
$(\ln P_{\text{passenger}})^3$	0.1020**	-12.2989***	-12.2840***
	(0.0480)	(0.0514)	(0.0508)
Strike Day	0.2893***	0.2903***	
	(0.0152)	(0.0153)	
Strike Participation Rate			1.4767***
			(0.0801)
Route×Price	No	Yes	Yes
Linear Time Trend	Yes	Yes	Yes
Route FE	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
N	73249	73249	73249
R^2	0.734	0.876	0.877
No. of Routes	82	82	82

Standard errors are in parentheses and are clustered by Routes.
* $p < .1$, ** $p < .05$, *** $p < .01$

4.7 Effects of Strike on Ridesharing Consumer Surplus

We focus our analysis on the consumer (passenger) side for welfare analysis. Our work does not assert that the strike increases passenger well-being. Furthermore, we are unable to estimate the true welfare loss due to the strike as we have no information on SNCF pricing, booking information, and train schedules during the strike period. However, by looking at the transaction data of BlaBlaCar, we could first calculate the increase in transaction value on strike days compared to non-strike days. The fact that BlaBlaCar creates more economic value during the strike implies that it recovers part of the economic loss due to the strike. We then further explore the changes in consumer surplus during the strike days. Based on the observed demand curves, we employ a novel approach to estimate the true market demand curve and to compute the consumer surplus. We then provide a range of consumer surplus estimates and the increase in consumer surplus on an average strike day.

4.7.1 Change in Transaction Values

In the previous section we already constructed the observed demand curves, which plots the demand at each price level for a given route on a given day. To calculate the transaction value, we only need to calculate the area under the observed demand curve, as shown in Figure 4.9. Since the strike increases the number of transactions, D_{strike} should lie to the right of $D_{\text{non-strike}}$. Note that there are no observed transactions outside the upper P_{upper} and lower price P_{lower} limits. The difference between the two curves is the increase in transaction value for a given route on a strike day compared to a non-strike day.

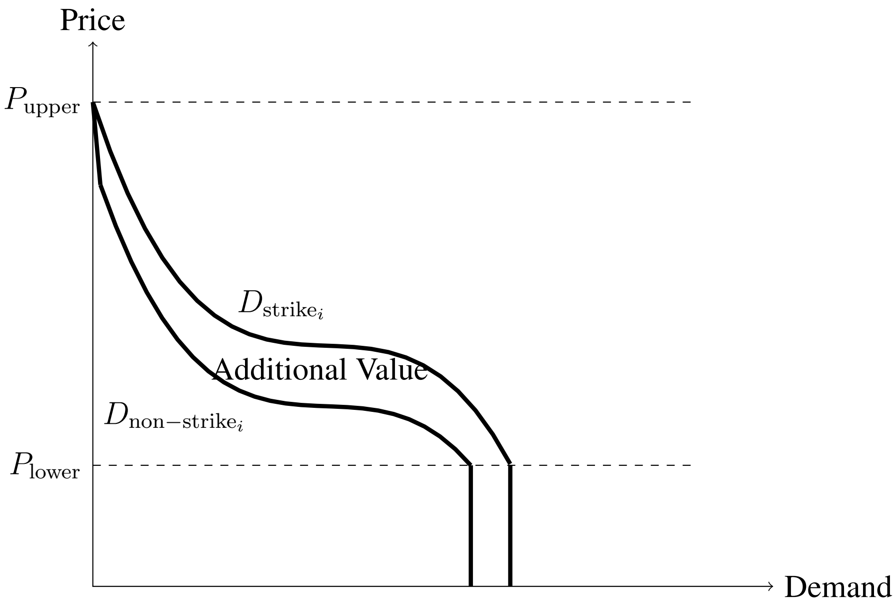


Figure 4.9: Illustration of Theoretical Observed Demand Curves of An Average Non-Strike Day ($D_{\text{non-strike}_i}$) and of An Average Strike Day (D_{strike_i}) of Route i.

No transaction is possible beyond the upper and lower price limits. The shadowed part represents the additional transaction value induced by the strike.

Table 4.4 presents the summary statistics of transaction values. The transaction value is higher by 25% on an average strike day than an average non-strike day. The table also reports the transaction values of different route segments according to the reference prices. Note that reference price is positively correlated with the trip distance. We divide all routes into three similar-sized segments: those with a reference price less than or equal to 6 €, those with a reference price larger than 14 € and those in-between. Most of our trips are not very costly. Not surprisingly, trips with higher prices contribute more to the total transaction and average daily transaction values. The average daily transaction amount for strike days of each route segment is higher than that for non-strike days, which is consistent with the result of all routes combined. The increase in the transaction value is higher (30%) among shorter routes.

Table 4.4: Summary Statistics of Transaction Value (April to July, in Thousands €)

	Total Transaction	Number of Days	Average Daily Transaction
Non-strike Days			
All Routes	8565	86	99.6
Ref price ≤ 6	867	86	10.1
$6 <$ Ref price ≤ 14	2128	86	24.7
Ref price > 14	5570	86	64.8
All Routes (April to June)	5550	55	100.9
Strike Days			
All Routes	4479	36	124.4
Ref price ≤ 6	470	36	13.1
$6 <$ Ref price ≤ 14	1062	36	29.5
Ref price > 14	2947	36	81.9

To estimate the impact of the strike, we estimate the following model:

$$\ln(V_{it}) = a + b\,\text{Strike}_t + \boldsymbol{x'}_{it}\boldsymbol{c} + e_{it} \tag{4.3}$$

here V_{it} is the area under the observed market demand curve of route i on the day t, Strike_t is the strike day indicator, the vector $\boldsymbol{x}_{it}$ contains the control variables including a linear time trend as well as the route, month, weekday and national holiday fixed effects, the vector $\boldsymbol{c}$ contains those corresponding coefficients, and the error term e_{it} is randomly distributed with a zero mean. We are interested in b, the coefficient of Strike_t, since it indicates the average impact of the strike on the total transaction value. The results are shown in Table 4.5. Column (1) reports the result where all routes share the same time trend. The strike significantly increases the daily transactions value by 25.2 percent, fairly close to the difference in the averages. Column (2) replaces the common time trend by route-specific time trends. The estimate of the daily transaction value remains significant and is almost identical to column (1). Column (3) replaces the strike day indicator by the overall strike participation rate. Multiplying the estimate by the average strike participation rate, which is 20 percent, the average impact is thus 25.2 percent. The three estimates are quite close to each other, and we could conclude that the average impact is roughly 25 percent.

Table 4.5: Impact of SNCF Strike on Transaction Value (Change in Percentage, with Commission)

	(1)	(2)	(3)
Strike Day	0.2520***	0.2516***	
	(0.0169)	(0.0168)	
Strike Participation Rate			1.2587***
			(0.0874)
Linear Time Trend	Yes	Route-specific	Route-specific
Route FE	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
N	9966	9966	9966
R^2	0.375	0.406	0.410
No. of Routes	82	82	82

Standard errors are in parentheses and are clustered by Routes.

* $p < .1$, ** $p < .05$, *** $p < .01$

4.7.2 Estimation of Consumer Surplus

Using the total transaction value as a measure of welfare may not be satisfactory because it implies that the true market demand curve (the maximum willingness to pay) is the same as the observed demand curve (the actual payments). This section estimates the consumer surplus by estimating the true market demand curve. As the area under the observed demand curve is exactly the total payments, the consumer surplus is the area between the two curves.

The standard approach to measuring consumer surplus relies on an equilibrium analysis. Economists aggregate information of transactions at either daily, weekly, or other levels, and treat the average as the equilibrium intersection of demand and supply. The oft-applied identification strategy is to take supply shocks as instrumental variables to identify the demand curve. We believe that with the data we have, and more generally any data collected by digital platforms, we can avoid aggregating information and construct a demand curve using transaction-level data. Aggregation is not even appropriate in the case of BlaBlaCar. Due to the existence of the reference price, the average price of each route varies within a very narrow range around the reference price. The traditional method would give us a very flat demand curve since many drivers sell their service at the reference price that mostly dominates the calculation of the average price. The conventional method would give us a counter-intuitive result as a considerable section of the very flat demand curve may lie below the transaction curve. Our challenge in this paper is to develop another approach to estimating the market demand curve that utilizes the transaction-level information and corrects the reference price bias.

A reference for demand curve estimation using transaction-level data is P. Cohen et al. (2016), in which they use the discontinuity of the Uber pricing strategy to observe the willingness to pay for passengers with similar profiles under similar ride-hailing situations. As they not only observe the accepted trips but also the abandoned ones, they can estimate the price elasticity of demand at each price discontinuity point and build the market demand curve over a range of prices.

We start by assuming a constant price elasticity of demand. Although the constant-elasticity assumption tends to oversimplify the real world, the advantage is that once we obtain a reliable estimate of the price elasticity of demand, we can draw the whole demand curve with an estimate of the intercept term. We assume the "true" market demand function as follows:

$$Q_{it}^m = K_{it}D(p_{it}^m) = K_{it}p_{m,it}^\eta \tag{4.4}$$

where Q_{it}^m is the market demand of route i on day t, D is a function of maximum willingness to pay ($p_{m,it}$), which takes the form of $(p_{it}^m)^\eta$, and the parameter η is the price elasticity of demand. For simplicity, we start by assuming that the price elasticity of demand is the same across routes and days, and will move on to estimate route-specific elasticities after. K_{it} captures the route and day fixed effects that affect the demand of the service of route i of day t. In other words, the demand curve is a line where η is the price elasticity of demand and $\ln(K_{it})$ is the x-intercept in a log-log space:

$$\ln(Q_{it}^m) = \ln(K_{it}) + \eta\ln(p_{it}^m) \tag{4.5}$$

We envisage that the observed market demand curve is a fraction of the true market demand curve in a sense that transaction price is a fixed fraction of its corresponding maximum willingness to pay. More precisely, we assume that the relationship between the transaction price and maximum willingness to pay given a demand is as follows:

$$\frac{p_{it}^m}{p_{it}} = \delta_{it} \tag{4.6}$$

where $\delta_{it} > 1$. Therefore, we assume that the observed demand has the following functional form:

$$Q_{it} = k_{it}D(\delta_{it}p_{it}) \times S(p_{it} - \mathrm{Com})^\theta \times \exp\epsilon_{it}. \tag{4.7}$$

To better interpret this relationship, we transform 4.7 into its natural-logarithm form:

$$\ln(Q_{it}) = \ln(k_{it}) + \eta \ln(\delta_{it}) + \eta \ln(p_{it}) + \theta \ln(Q^s_{it}) + \epsilon_{it}. \tag{4.8}$$

Excluding the error term, the right-hand side can be divided into three components. Firstly, $\eta \ln(p_{it})$ captures the relationship between the price and demand. In other words, in a log-log space, η is the slope of the demand curve. The assumed equation implies that the price elasticity of the observed demand is the same as that of the true demand:

$$\frac{dQ}{dp}\frac{p}{Q} = \frac{dQ^m}{dp^m}\frac{p^m}{Q^m} = \eta \tag{4.9}$$

Secondly, $\theta \ln(Q^s_{it})$ captures the horizontal impact of the supply condition on the demand curve. The supply condition enters into the picture because the observed demand is constrained by the availability of seats at a given price. For instance, we would very probably observe a rise in demand at a certain price during a particular day because of an increase in supply at that price. The last component $\ln(k_{it}) + \eta \ln(\delta_{it})$ is the route-day specific fixed effect. Since we observe p_{it}, Q^s_{it}, and Q_{it}, regressing Equation (4.8) gives us an estimate of η, which is the price elasticity of demand of the actual market demand, and $\ln(k_{it}\delta^{\eta}_{it})$ is thus the route-day-specific constant term, which corresponds to the route-day fixed effects obtained by the regression.

Figure 4.10 is helpful in illustrating our proposed approach. The observed demand curve Q (the regression line) lies below the true demand curve Q^m and they share, by assumption, the same slope η. By regression, we obtain the estimated value of $\ln(k_{it}\delta^{\eta}_{it})$, which can be considered as the x-intercept of the observed demand. To measure the consumer surplus, we are however not concerned with $k_{it}\delta^{\eta}_{it}$ but K_{it}. The ranking of $k_{it}\delta^{\eta}_{it}$ across routes and days is important for us to deliver an educated guess of the ranking of K_{it}. We assume that their rankings are exactly the same. To give a conservative estimate, we constrain K_{it} by assuming that the smallest consumer surplus across all routes and days is at least zero. Furthermore, we can roughly deduce δ_{it} by the following formula:

$$\delta_{it} = 1 + \frac{p_{m,it} - p_{it}}{p_{it}} \approx 1 + \frac{\text{Consumer Surplus}}{\text{Transaction Value}} \tag{4.10}$$

To compute an estimate of the x-intercept term of the true demand curve, $\hat{K}_{it}$, we rely on a trial-and-error approach. We multiply the estimated route-day fixed effects of the regression of the observed

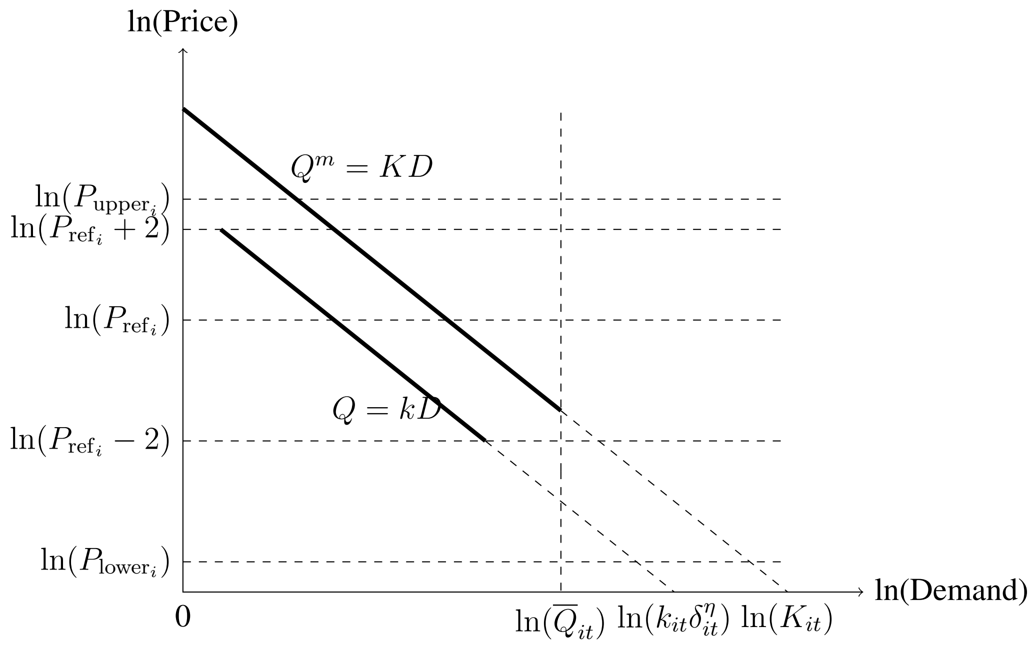


Figure 4.10: Illustration of A True Demand Curve (Above) and An Observed Demand Curve (Below)

We propose to estimate the slope of the observed demand based on the sample of observations within the range of 2 € above and 2 € below the reference price, and assume that this estimated slope is equal to the slope of the true demand curve.

demand curve by a multiplier ϕ, and compute the consumer surplus of all routes of all days. If any computed consumer surplus is negative, we try a larger multiplier and repeat the calculation until all consumer surpluses are non-negative.

The next section is dedicated to the estimation of η, in which we compare several methods that aim to resolve the problems due to the existence of reference prices.

Estimation of Price Elasticity of Demand for All Routes

As drivers are encouraged to set prices at the recommended price, we observe spikes at the reference price for both the demand and supply curves, as shown in Figures 4.7 and 4.8. If we estimate price elasticity using observations, including those at the reference price level, the result would be unreliable because the spike creates an unusual flat section on the demand curve. Meanwhile, we could not use the observations that are too far from the reference price because offers (supply) are rare at those prices. At prices slightly above and below the reference price, for example, two euros above and two euros below, there are a reasonable number of offers available and transactions observed. The slope of the line linking the two price levels above, $[P_{\text{ref}} + 1, P_{\text{ref}} + 2]$, and the slope of that linking the two price levels below, $[P_{\text{ref}} - 2, P_{\text{ref}} - 1]$, are reasonably representative for estimating the price elasticity of demand. As a result, we drop the routes which have a reference price equal to or lower than 2 €, and 78 routes remain in our sample.

To deal with the distortion produced by the recommended price, we propose several methods. These methods will be compared side-by-side as a robustness check and allow us to obtain a robust range of estimates.

For Method A, we use the observations of the ranges $[P_{\text{ref}}+1, P_{\text{ref}}+2]$ and $[P_{\text{ref}}-2, P_{\text{ref}}-1]$, while leaving out those at the reference prices, to estimate the price elasticity of demand, without considering the supply condition for the moment, in which we smooth the impact of the supply peak by taking out the observations at the peak. We control for the weekday, month, national holiday, and route fixed effects, a linear time trend, and also indicators of whether an observation is above or below the reference price.[19]

Method A is not satisfactory in the sense that we drop observations at the reference prices instead of trying to correct the bias induced by the recommendation. For Method B, we correct this by including those observations and run the same regressions using observations of $[P_{\text{ref}} - 2, P_{\text{ref}} + 2]$. We expect Method B to give a more elastic estimate.

For the Method C, we use the same data as Method B, and we add three price indicators in the regression: above the reference level, at the reference level, and below the reference level. The indicators help to correct the spike of the supply at the reference level, as well as the relative shortage of supply below the reference price. Method D includes the natural-logarithmic form of the supply to capture the impact brought by the supply condition. Finally, Method E amends Method D by adding an interaction between the supply and the routes. Results are shown in Table 4.6.

As expected, Method B produces a higher price elasticity ($\hat{\eta}$ = -4.68) than Method A. Adding section indicators drags the estimated elasticity back to a similar level as Method A. However, once we control for the supply, we again obtain a higher elasticity estimate ($\hat{\eta}$ = -4.82 for Method D and -5.16 for method E). Also, the effect of the strike decreases since the change in supply absorbs some of its effects. We proceed with the elasticity estimation of Method D for the calculation of the consumer surplus since it gives a moderate estimate of η while relying on fewer co-variates than Method E.

[19]The inclusion of section indicator variables allows the intercept to differ so that the slope of the demand curve (elasticity) will not be a linear average of observations of the four price levels, but the average of two linear averages of observations of the two sections.

Table 4.6: Estimation of Unified Price Elasticity of Demand (η) for 78 API-Collected Routes

	(1) MethodA	(2) Method B	(3) Method C	(4) Method D	(5) Method E
η	-2.2372***	-4.6848***	-2.2289***	-4.8244***	-5.1554***
	(0.3458)	(0.2466)	(0.3377)	(0.3437)	(0.3643)
Strike Day	0.2750***	0.2710***	0.2719***	0.2263***	0.2256***
	(0.0145)	(0.0142)	(0.0139)	(0.0130)	(0.0127)
At Ref. Price			0.8898***	0.7299***	0.7054***
			(0.0342)	(0.0365)	(0.0430)
Below Ref. Price	0.9237***		0.9253***	1.1474***	1.0437***
	(0.0719)		(0.0705)	(0.0589)	(0.0588)
ln Supply				0.4985***	0.6259***
				(0.0223)	(0.0298)
Linear Time Trend	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Route-specific Supply	No	No	No	No	Yes
N	32266	41762	41762	41762	41762
R^2	0.777	0.716	0.778	0.838	0.852
No. of Routes	78	78	78	78	78

Standard errors are in parentheses and are clustered by Routes.

* $p < .1$, ** $p < .05$, *** $p < .01$

Calculation of the Consumer Surplus Using the Estimated Elasticity

As mentioned earlier, the consumer surplus of each route on each day equals the difference of the total transaction value (the area below the observed demand curve) and the area below the market demand curve (see Figure 4.11 for an illustration).

For the convenience of calculating the former, we firstly transform Equation 4.4 as follows:

$$p_{it}^m = \left(\frac{Q_{it}^m}{K_{it}}\right)^{\frac{1}{\eta}}. \tag{4.11}$$

The consumer surplus CS_{it} of route i on day t is thus the integration of p_{it}^m over the quantities transacted minus the transaction value:

$$\mathrm{CS}_{it} = \int_0^{\overline{Q}_{it}} \left(\frac{Q^m}{K_{it}}\right)^{\frac{1}{\eta}} dQ^m - V_{it} \tag{4.12}$$

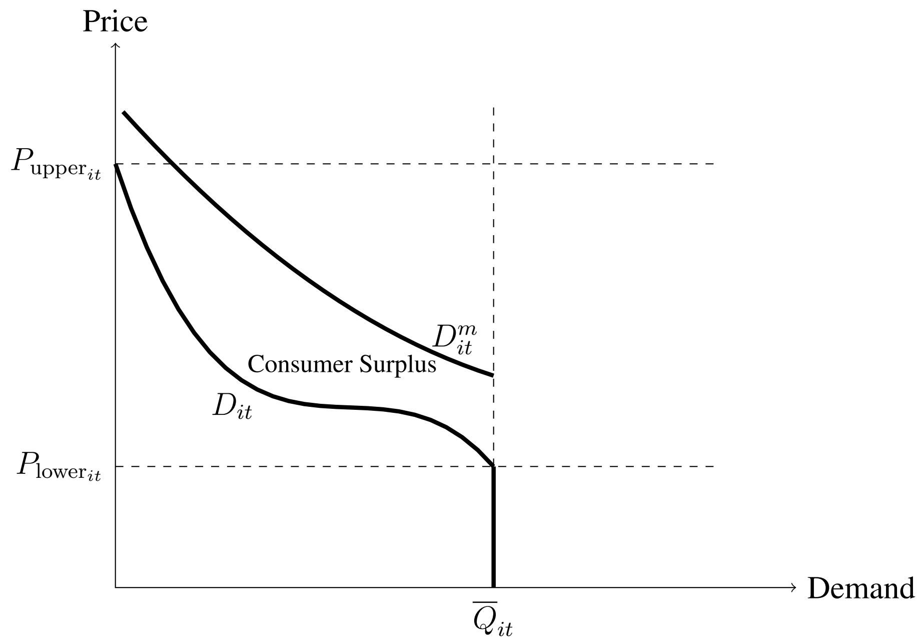


Figure 4.11: Illustration of the Computation of the Consumer Surplus

The area under the observed demand curve D_{it} is exactly the total payment of all bookings. The area between D_{it} and D^m_{it} denotes the consumer surplus.

where $\overline{Q}_{it}$ is the observed demand at the lower price limit of route i.[20]

Equation 4.12 can be transformed as follows:

$$\text{CS}_{it} = \lim_{c \to 0^+} \int_c^{\overline{Q}_{it}} \left(\frac{Q^m}{K_{it}}\right)^{\frac{1}{\eta}} dQ^m - V_{it} = \frac{1}{K_{it}^{\frac{1}{\eta}}} \frac{1}{\frac{1}{\eta}+1} \overline{Q}_{it}^{\frac{1}{\eta}+1} - V_{it}. \tag{4.13}$$

Note that η cannot be larger than -1. Otherwise, the integral is undefined. We have already calculated V_{it} and estimated η. By using the trial-and-error approach outlined above, we obtain $\hat{K}_{it}$. The multiplier ϕ is 23. We then summarize the estimated consumer surplus in Table 4.7 using method D. The difference in the estimated consumer surplus between an average strike and non-strike day can be interpreted as the additional consumer welfare gain of the strike due to BlaBlaCar, which is 7,847 €.

Table 4.7: Summary Statistics of Estimated Consumer Surplus of API-Collected Routes: Unified η Using Method D (April-July 2018, in €)

	Total CS	Average Daily CS	Average δ^*
Non-strike Days (86 days)	3,357,898	39,045	1.527
Strike Days (36 days)	1,688,100	46,892	1.503

$^*\delta_{it}$ is one plus the ratio of the consumer surplus estimate and the total transaction value of a route per day

[20]Note that the integral does not go beyond the demand at the lower limit. It is because there is no transaction below that limit and we estimate consumer surplus generated by actual transactions.

Table 4.8 reports the results of the regressions of the natural-logarithm transformation of the consumer surplus on a strike indicator using Method D. The control variables remain the same as in Table 4.5, and so do the specifications of each column. On average, the strike leads to a significant increase in the consumer surplus by 21 percent, which is in line with the summary statistics and is robust across three specifications. The result again suggests that there were considerable substitutions during the strike period.

Table 4.8: Impact of SNCF Strike on BlaBlaCar Consumer Surplus: Unified η Using Method D (Change in Percentage)

	(1)	(2)	(3)
Strike Day	0.2136***	0.2135***	
	(0.0058)	(0.0058)	
Strike Participation Rate			0.9704***
			(0.0293)
Linear Time Trend	Yes	Route-specific	Route-specific
Route FE	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
N	9508	9508	9508
R^2	0.621	0.638	0.629
No. of Routes	78	78	78

Standard errors are in parentheses and are clustered by routes.
Consumer surpluses are calculated using prices with commission.
* $p < .1$, ** $p < .05$, *** $p < .01$

Estimation of Route-Specific Elasticity

The analysis of the previous section relies on the assumption that the price elasticities of all routes are the same. However it is likely that the price elasticity varies significantly across the routes. We build upon Method D of the previous section and add interactions of the price levels (log-transformed) with the routes, and thus obtain route-specific elasticities, as summarized in Table 4.9. The routes are ranked in ascending order according to the η obtained, with the smallest (most elastic ones) at the top. In general, we find longer, more expensive routes ranked at the top.

Table 4.9: Estimation of Route-Specific Elasticity (η) of 78 API-Collected Routes

Route	η	Ref. Price	Route	η	Ref. Price
Lyon Paris	-14.4459	30	Paris Rouen	-7.5839	9
Paris Toulouse	-13.5969	43	Pau Bordeaux	-7.4475	13

Paris Marseille	-13.5819	49	Bordeaux Pau	-7.4097	13
Toulouse Paris	-13.4097	43	Rennes Nantes	-7.3235	7
Lyon Bordeaux	-13.0054	36	Nantes Rennes	-7.0712	7
Strasbourg Paris	-12.7287	31	Strasbourg Metz	-7.0447	10
Marseille Paris	-12.7212	49	Metz Strasbourg	-6.8219	10
Paris Strasbourg	-12.6069	31	Reims Paris	-6.6860	9
Bordeaux Lyon	-12.2521	36	Paris Reims	-6.5072	9
Paris Nantes	-12.2285	24	Nantes Angers	-6.4979	5
Nantes Paris	-12.0027	24	Carcassonne Toulouse	-6.4611	6
Paris Lyon	-11.4755	29	Tours Poitiers	-6.4242	6
Toulouse Marseille	-11.3300	26	Rouen Le-Havre	-6.3116	5
Marseille Toulouse	-11.1427	26	Le-Havre Rouen	-6.2814	5
Bordeaux Paris	-10.9133	37	Angers Nantes	-6.2771	5
Rennes Paris	-10.4403	22	Poitiers Tours	-6.1972	6
Paris Bordeaux	-10.3112	37	Toulouse Carcassonne	-6.1864	6
Bordeaux Toulouse	-10.1649	15	Grenoble Lyon	-5.9758	6
Montpellier Toulouse	-10.1222	15	Lyon Grenoble	-5.9604	6
Marseille Lyon	-9.9986	20	Tours Le-Mans	-5.8152	6
Toulouse Montpellier	-9.9728	15	Le-Mans Tours	-5.7854	6
Paris Rennes	-9.9532	22	Paris Amiens	-5.7074	9
Lyon Marseille	-9.8463	20	Amiens Paris	-5.6846	9
Toulouse Bordeaux	-9.7392	15	Avignon Marseille	-5.6035	6
Caen Rennes	-9.5767	12	Chambéry Lyon	-5.5685	6
Rennes Caen	-9.2820	12	Marseille Avignon	-5.5018	6
Lille Paris	-9.2395	14	Lille Calais	-5.4144	7
Paris Lille	-9.0464	14	Lyon Chambéry	-5.4135	6
Poitiers Bordeaux	-9.0369	16	Rennes Saint-Malo	-5.1794	4
Bordeaux Poitiers	-8.6374	16	Calais Lille	-5.1419	7
Montpellier Marseille	-8.5968	11	Saint-Malo Rennes	-5.1408	4
Dijon Lyon	-8.4970	13	Besançon Dijon	-4.7543	6
Lyon Dijon	-8.2814	13	Dijon Besançon	-4.6775	6
Marseille Montpellier	-8.0460	11	Toulon Marseille	-4.3719	4
Lyon Clermont-Ferrand	-7.9874	10	Marseille Toulon	-4.2801	4
Le-Mans Paris	-7.7726	13	Nîmes Montpellier	-3.0831	3
Paris Le-Mans	-7.7560	13	Montpellier Nîmes	-2.9397	3
Rouen Paris	-7.7534	9	Metz Nancy	-2.3487	3
Clermont-Ferrand Lyon	-7.7134	10	Nancy Metz	-2.2846	3

Apart from the price elasticity, the new regression also gives new estimates of the intercept term of the regression of the observed demand. Based on these two new pieces of information, we re-compute the consumer surplus of each route per day, as shown in Table 4.10.[21] The average consumer surplus estimate is smaller, dropping from 39,045 € to 22,308 € on an average non-strike day and from 46,892 € to 26,507 € on an average strike day, although the percentage increase of consumer surplus on an average strike day is similar. We expect the drop in the consumer surplus as allowing some routes to be more elastic means a sharper fall in demand along the demand curve. It turns out that a majority of routes have

[21] The multiplier ϕ is now 38.

a more elastic demand than the overall estimated demand. Accordingly, δ, the ratio of the maximum willingness to pay to the payment, is slightly smaller than that estimated with a route-invariant η.

Table 4.10: Summary Statistics of Estimated Consumer Surplus of API-Collected Routes: Route-Specific η Using Method D (April-July 2018, in €)

	Total CS	Average Daily CS	δ^*
Non-strike Days (86 days)	1,918,472	22,308	1.474
Strike Days (36 days)	954,271	26,507	1.442

$^*\delta_{it}$ is one plus the division of consumer surplus estimate by total transaction value of a route per day.

4.8 Extension to Routes Not Included in the API Collection

In previous sections, we calculated the impact of the strike on the demand, supply, and estimated consumer surplus based on the observed data of either 82 or 78 routes. Although we carefully choose these routes to be representative of different regions of France, their scale is insufficient for us to give an estimate of the impact of BlaBlaCar of the whole of France. This section attempts to extend our estimation to more routes and to give a closer estimate of the contribution of BlaBlaCar for the whole of France. The steps are as follows. Firstly, we choose 318 additional routes that include links between smaller cities and routes linking smaller cities to major cities. Of course, we can never exhaust all the possible routes, but we try to include the more frequented routes. From now on, we will refer to the original 78 routes as the observed set and the other 318 routes the unobserved set. Secondly, we employ three methods to impute the consumer surplus estimates of the unobserved routes.

4.8.1 Selection of Additional Routes

For the initial 78 routes, we chose the largest French cities and constructed direct routes between them (without passing by another city on the list). To enlarge the sample size, we follow the same logic to include more cities based on their sizes.

France is exceptionally complex in its administrative construction. We appeal to the definition of urban areas (*Aire Urbaine* in French) to select new routes. An urban area is a cluster of cities, with one city as the primary employment basin, which on its own offers more than 10,000 jobs, and with other smaller cities nearby, of which at least 40% residents work in the primary employment basin city. From INSEE (the French national statistical agency), we obtain the population information of the urban areas as of 2016. These urban areas separate France into non-overlapping clusters, with one center for each cluster, which helps us identify the most active cities in France.[22] Since it is not the residential but working behavior that defines the urban areas, this definition captures the extent of economic activities, and thus gives us a better idea of the potential adverse impact of the SNCF strike.

We decide only to include urban areas with more than 75,000 residents in 2016, which gives us 114 urban area center cities. We could continue to include smaller urban areas or even to include all of them (there are around a thousand), but it would lead to a very long list of routes, which might have no transactions for most days. Besides, the results from the observed set may not be relevant for small urban areas as their characteristics differ substantially. We investigate some smaller urban areas on the BlaBlaCar website, and the lack of offers supports our decision. Not choosing urban areas below 75,000 residents is thus a compromise between completeness and simplicity. Figure 4.12 shows the geographic representation and population of the selected urban areas.

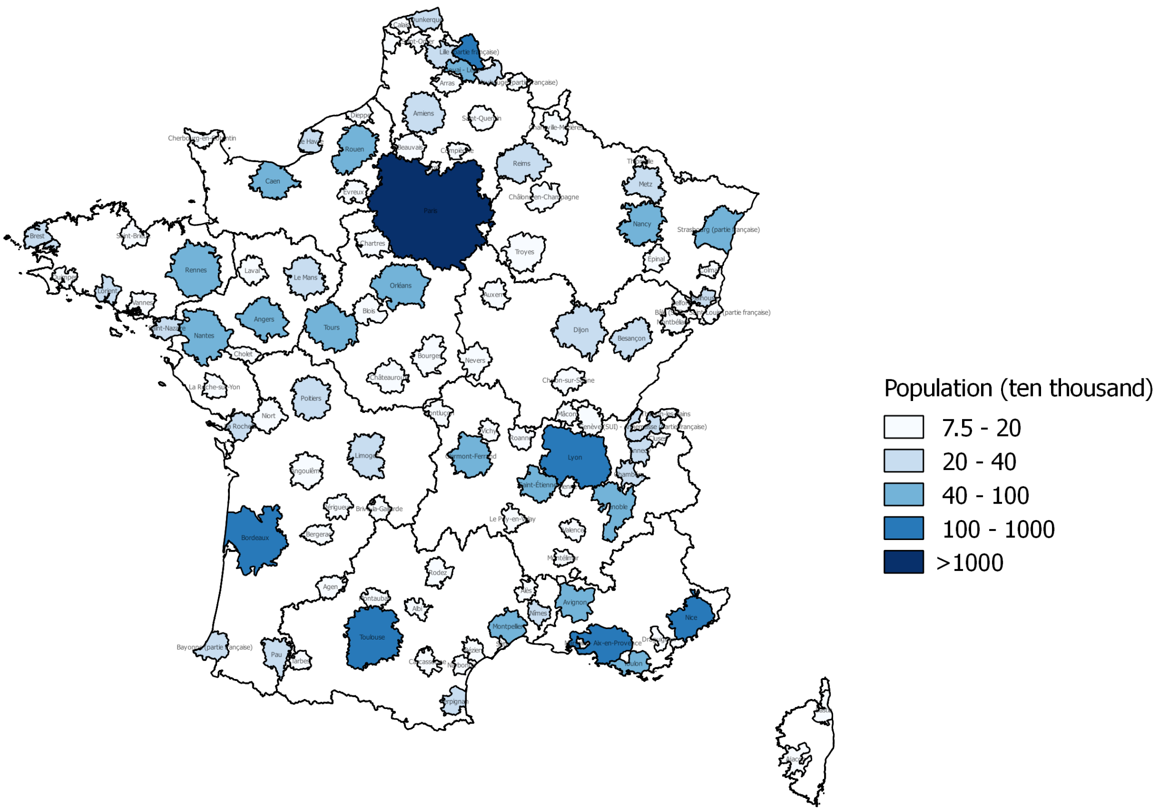


Figure 4.12: Urban Areas with More than 75,000 Residents

Once we have the list of urban areas, we start building the route list. We firstly list all routes that connect the two principal cities of neighboring urban areas. By doing so, we include smaller routes that

[22]Due to this definition, some more remote cities belong to no urban area, because the employment of their residents is dispersed over several cities so that no one city attracts more than 40%, but the exclusion of these cities has little impact on our analysis.

are not already segments of other routes. We then exclude the routes that are already in the initial list and the routes that are too improbable for ridesharing. We do so by verifying each route on the BlaBlaCar website to see if there are regular posts. In the end, we include 159 new pairs of cities, thus 318 new routes. The list of the new routes is available in Appendix C.8.

4.8.2 Route Characteristics

Our next step is to collect data on the route characteristics to impute the missing consumer surplus estimates. The first set of data is the economic and socio-demographic data of the departure and arrival cities. INSEE offers useful data at different levels.[23] We collect the GDP per capita in 2015 at the city level as well as the unemployment rate in 2018 at the *departement* level.

The second set of data is the transportation data related to the ridesharing and train modes, such as the default price, upper, and lower price limits, as well as the distance of each route. Whether the route is served by SNCF, and the price and travel time information are also crucial for transport modal choice. We collect this information from the SNCF website, including whether there is a direct TGV (high-speed railway), whether there is a direct TER (inter-regional train), the most common travel time, and the most common price of the route by train.[24] Table 4.11 compares initially observed routes and the unobserved routes on several route characteristics. We can see that newly added routes are shorter, and the connecting cities are less affluent, smaller in population, and generally less well-off economically. The comparison suggests that we should take the selection bias into account.

4.8.3 Imputation Models of Consumer Surplus of the Unobserved Sample

Recall that our objective of this section is to estimate the consumer surplus of each unobserved route each day from April to July 2018. As the official BlaBlaCar data for those unobserved routes have been deleted from the API, we impute those missing values by two main approaches. Readers may be concerned with selection bias. If the unobserved routes are quite different from the observed routes in terms of some characteristics, imputation based on the observed sample may produce biased values as

[23] See https://statistiques-locales.insee.fr/#c=indicator&view=map1.

[24] Train prices change all the time. Train travel time differs according to the train speed and the route. It is impossible to come up with one standard train price or travel time of a route. Our approach is to choose the most commonly occurred train type, and the non-discounted price for an average passenger for a hypothetical future departure date. If the route has a frequent direct TER service (Inter-Regional Express, usually connects second-tier cities and slower than the TGV), we then choose its regular price because this does not change even approaching the departure time. If the route has a frequent direct TGV service (High-Speed Railway), whose price varies a lot, we will choose the lowest price for a future departure date.

Table 4.11: Comparison of Characteristics of Observed (API-Collected) and Unobserved Samples

	Observed		Unobserved		
No. Routes	78		318		
	Mean	SD	Mean	SD	t-stat
Default Price	14.526	11.645	6.553	2.636	6.01
Distance (km)	230.615	181.548	124.075	48.880	5.15
ln(GDP per capita)*	20.719	0.313	20.537	0.189	4.92
ln(Population)*	27.850	1.703	25.349	1.116	12.34
Unemployment Rate*	75.870	27.559	82.828	30.981	-1.95

*They are the multiple of the log values of the departure and arrival cities.

linear prediction assumes the same linear relationship between the dependent and independent variables is found in the unobserved sample. To produce robust estimates, we will employ two different methods, and their values will deliver a safe range that includes the true, but unobservable, value.

The first method is a linear prediction of the consumer surplus based on the values obtained in the observed sample with route-specific elasticity (Table 4.10). We regress the consumer surplus estimate obtained in the previous section on route-specific characteristics, including the log of the distance between the departure and arrival cities, the multiple of the log of the population, the multiple of the log of the GDP per capita, the multiple of the unemployment rate, whether having a direct TER line and whether having a direct TGV line. As the number of combinations of the independent variables is infinite considering all polynomials, we limit the set of models by fixing the maximum order of polynomials to two. Moreover, we allow only interactions of route-specific variables, leaving aside time-variant variables. Next, we regress all these possible combinations and select the best five models.[25] To select the best prediction model, we employ a k-fold cross-validation (Zhang & Yang, 2015). In brief, k-fold cross-validation randomly divides a sample into k folds of equal size and fits the model on $k-1$ folds while taking the remaining fold as a validation set. As a result, we conduct k tests and select the best model among a set of models based on the average performance of minimizing root-mean-square error (RMSE). Despite being increasingly challenged, we take $k = 10$ as most researchers advise (Arlot & Celisse, 2010). We tried some other values of k, and the conclusion of the model selection does not change. We choose the best model that gives the least average RMSE to predict to impute the values of the consumer surplus of the unobserved routes.

To better address the potential selection bias, we adopt the same cross-validation process to compute

[25]The selection is made by the Stata package *bfit*, which ranks all models by BIC (Bayesian Information Criterion).

a propensity score of "being included in the first round" for both observed and unobserved routes, and then insert this propensity score into the regression equation for the consumer surplus as a covariate. We produce results without (Method 1a) and with (Method 1b) the propensity score as a covariate. The second method is a direct application of propensity score matching. For each unobserved route, we match it with the nearest neighbor within the set of observed routes according to the propensity score and borrow its consumer surplus estimate. The advantage is that the resulting estimates will always fall within the range of estimates of the observed sample, ruling out unexpected spikes or dips in values due to the misspecification of the prediction model.

For brevity, we only present some summary statistics of the results in the main text but not the selection process, as shown in Table 4.12.[26] Columns (1)-(3) reproduce the results from the previous sections. Method 1a (regression-based linear prediction) produces a reasonable estimation. The average consumer surplus on a non-strike day is 57,285 €, 2.57 times the result of the observed sample. Although the number of newly added routes is four times larger than the number of observed routes, the increase is roughly correct considering the smaller scale of those unobserved routes. On an average strike day, the total consumer surplus reaches 73,598 €. In other words, BlaBlaCar recovers 16,313 € consumer surplus on an average strike day. Including also the propensity score as a covariate (Method 1b), however, pushes the non-strike and strike day consumer surplus estimates up to 88,064 € and 105,987 € respectively. The values are perhaps too large as they are almost four times the total of the consumer surplus of the scraped set. Finally, Method 2 (Nearest-neighbor propensity score matching) produces a moderate result (79,413 € and 97,166 € for the non-strike and strike days respectively).

Based on Method 2, we can give a rough estimate of the consumer surplus generated by BlaBlaCar in a year. Suppose there were no strikes in a given year. On an average day from April to July, BlaBlaCar generates 79,413 € consumer surplus. If this figure is also applicable to the other months of the year, then a year of 365 days generates in total 29 € million (approximately US$25.3 million) consumer surplus. For comparison, SNCF Voyageurs generates 16.36 € billion revenue in France in 2018.[27] Our yearly estimate of the consumer surplus seems small (1.77%), but they are not certainly operating at the same scale.

[26]The selected models are given in the Appendix C.7.

[27]Retrieved on 10 February 2020 at https://medias.sncf.com/sncfcom/finances/Groupe_SNCF/SNCF_GROUPE _Investor_Presentation_jan.2020.pdf .

Table 4.12: Estimation of the Consumer Surplus of All 396 Routes, Method Comparison (April-July 2018, in €)

	(1)	(2)	(3)	(4)	(5)	(6)
Average Daily	Transaction	Unique η	Route η_i	Method 1a	Method 1b	Method 2
No. of Routes	78	78	78	396	396	396
Non-strike	99596	39045.33	22307.81	57277.29	88046.08	79413.29
Strike	124414	46891.67	26507.54	73616.55	105998.47	97166.11
Difference	24818	7846.34	4199.72	16339.26	17952.39	17752.82
% Change	0.249	0.201	0.188	0.285	0.204	0.224

The first three columns reproduce the results from previous sections, which rest upon data of the scraped sample. Columns (4)-(6) extend our consumer surplus estimation to the 318 additional routes. Method 1 refers to regression-based linear prediction, without (1a) and with (1b) propensity score as a covariate. Method 2 refers to nearest-neighbor propensity score matching.

4.9 Cost and Welfare Comparison

This section continues the discussion by extending to other welfare impacts, such as time and environmental costs, that are taken into account by individuals and possibly a social planner. Individuals may not be consciously aware in their individual choices of the environmental costs of their mode of transport. In other words, the individual may not care about the externalities due to their behaviors, as environmental costs are out of scope of their cost functions. We compare the overall the individual costs of taking trains and of ridesharing. More precisely, we calculate the total costs of a ridesharing driver C_d, a ridesharing passenger C_p and a train passenger C_t respectively in Equation 4.14 (with route subscripts omitted for clarity):

$$\begin{aligned} C_d &= (T_r + (n-1)/6) \times \omega_{\text{dep}} + f + \tau - (n-1) \times P_r \\ C_p &= (T_r + 1/6) \times \omega_{\text{dep}} + P_r + \text{Com} \\ C_t &= T_t \times \omega_{\text{dep}} + P_t \end{aligned} \tag{4.14}$$

where n is the number of people (including the driver) of a trip, T_r and T_t are the time costs spent on the trips by ridesharing and train, respectively, according to online Google Map simulations. We ignore the amortization costs of the car to focus on the marginal cost per ride. For ridesharing drivers, we add ten minutes per passenger because they need time to locate passengers. For each additional passenger, the time spent on the ride increases by $1/6$ hour. In total, the driver spends $(n-1)/6$ additional time. We approximate the time cost of the trip by multiplying the time spent on the trip by the hourly income of the corresponding departement ω_{dep}. In addition, drivers pay the fuel cost f and the toll fee τ, and receive payments P_r from the $n-1$ passengers.[28] We assume that prices that drivers earn per passenger are the reference prices, as the reference prices are usually the most frequently quoted prices. On the other hand, passengers do not pay the fuel and tolls but only the price P_r and commission Com through BlaBlaCar.[29] The time cost of taking a train is T_t, obtained from the SNCF official website, and the price is P_t is the most frequently observed price of each route.

Due to the lack of data, we do not include the costs related to noise and the leisure price of driving or of taking a train. We also consider the time spent on booking a seat on BlaBlaCar and on SNCF as equal and negligible compared to the time cost of a trip.

Table 4.13 lists the time, monetary, and overall costs of drivers and passengers with some summary statistics. The upper panel of the table shows the information of each component. The mean travel time of driving is similar to that of taking a train, although the tail to the right is longer. In general, the ridesharing price is much lower than the train fare.

The lower panel of Table 4.13 compares the total costs of different user profiles using Equation 4.14. Comparing ridesharing as a passenger and taking a train, ridesharing is, on average, 40% cheaper. We take the normal train ticket price as the reference that is available when booking reasonably in advance, and therefore its variation is less pronounced than the cost of a solo driver. We could imagine that as the departure date approaches, taking trains (especially high-speed trains) would become more expensive. On the other hand, the drivers' total costs drop substantially as a function of the number of passengers. Ridesharing with three passengers on average reduces the drivers' total costs by 38% compared to driving alone, providing evidence for the benefit of the sharing economy for reducing personal costs. A trip will cost a driver even less than a passenger if she shares with more than two passengers.

The data can also help us understand the modal choice. Figure 4.13 compares the total cost of a ridesharing driver, a ridesharing passenger, and a train passenger for different road distances. We separate the cost comparison of driving and taking trains in the left figure and the cost comparison between being a ridesharing passenger and taking trains in the right figure. Since most of the routes in our sample are

[28] We collect the information on fuel consumption per kilometer and fuel prices of the two main fuel types: petrol and diesel. The price of petrol is 1.48 € per liter in 2018 on average, while driving 100km would cost 7.18 liters of petrol, the equivalent of 10.63 € . The price of diesel is 1.39 € per liter in 2018 on average, while driving 100 km would cost 6.01 liters of diesel, the equivalent of 8.35 € . The weighted fuel cost is thus 9.49 € per 100km. The toll fee is retrieved in December 2019 from https://www.sanef.com/fr/tarifs-peage. On average, the toll fee has risen by 1.86% compared to 2018. However, since there may be difference in the rates of change for each route, we directly use the 2019 level as a proxy of the toll fee in 2018.

[29] See Appendix C.4 for the commission levels.

Table 4.13: Descriptive Statistics of Ridesharing and Train Costs of All 396 Routes (Without Environmental Costs, in €)

	Min	Max	Mean	Sd	P25	P50	P75
Car Time Cost (Solo Driver)	7.76	172.38	23.23	18.35	14.02	18.72	25.05
Car Fuel and Toll Costs (Solo Driver)	4.94	132.85	22.69	18.49	11.67	18.35	27.34
Ridesharing Price (per Passenger)	4	58	9.8	7.7	6	8.5	11
Train Time Cost	4.9	135.88	23	15.08	12.84	19.13	28.07
Train price (per Passenger)	7.5	58	21.97	10.2	14.5	19.05	28.9
Total RS Cost per Passenger	13.86	233.76	35.32	25.96	21.81	28.56	38.9
Total Cost of Driver (No passenger)	12.7	305.23	45.92	36.02	26.88	36.75	53.74
Total RS Cost of Driver (with 1 passenger)	11.8	259.6	40.09	29.86	24.11	32.46	46.33
Total RS Cost of Driver (with 2 passengers)	10.9	213.99	34.26	23.83	21	28.23	38.93
Total RS Cost of Driver (with 3 passengers)	9.99	168.37	28.42	18.03	18.29	23.76	31.75
Total Train Cost per Passenger	15.8	150.88	44.97	22.61	28.17	39.7	55.72

between neighboring cities, we have many more observations on the left-hand side of each figure than on the right-hand side. Even for similar distances, the total costs of taking trains vary considerably because of the different train types, while the costs of ridesharing drivers and passengers increase smoothly with distance. A potential driver could choose between taking a train and being a driver on BlaBlaCar. The decision will undoubtedly depend on the number of passengers on board. Referring to the left figure, if the driver drives alone (the black line), her total cost of driving is similar to taking a train (the blue line) when the trip is below 250 km. Above this distance, the cost of driving continues to grow while the cost of a train ride flattens out. However, if the driver could find three passengers to share the ride (the smooth grey line), her total cost as a driver would drops below the train cost level for trips shorter than 250 km. Beyond that distance, her cost increases at a much slower rate than driving alone. The cost continues to be comparable with the train passenger cost even at very long distances. Another important choice is for passengers to choose between ridesharing and taking a train. Referring to the right figure, the black line represents the total cost of a ridesharing passenger. Under 250 km, the cost of ridesharing is below that of taking a train but becomes more costly once the route is longer than 250 km, showing the disadvantage of ridesharing for long-distance travels.

So far, we have limited our analysis to the individual decision making. To give some implications from the social welfare perspective, we compare the environmental cost per person between taking a train and ridesharing. The SNCF official website provides CO_2 emission estimation per person of undertaking the trip by car and by train. Again, we choose the most frequently observed train line of a route as our benchmark.[30] As for the price of carbon, the French Ministry of the Environment sets the carbon price at

[30]https://www.sncf.com/fr/itineraire-reservation/itineraire In general, high-speed railways are more environmentally friendly than regional trains.

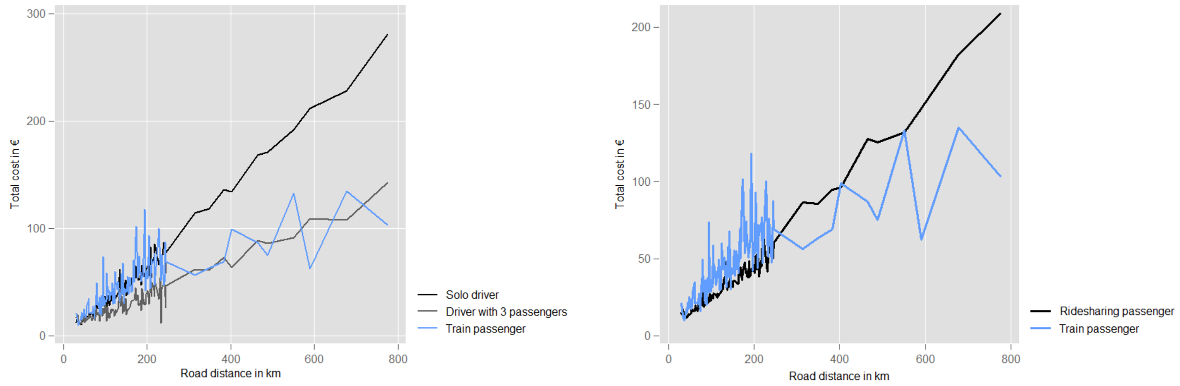


Figure 4.13: Total Costs of Ridesharing Drivers, Passengers and Train Passengers for Different Distances

39 € per ton of CO_2 in 2018.[31] Ricke, Drouet, Caldeira, and Tavoni (2018) propose that the social cost of carbon emission is roughly 378 €, ten times of the monetary price of carbon. As the data provided by SNCF assumes that the car's emission is for the entire trip, we split the total emission cost of the trip by n to estimate the individual environmental cost.[32]

Table 4.14 shows the socio-environmental cost per person for different profiles. Since ridesharing drivers and passengers equally share the environmental cost of the trip, we only present the environmental cost per person under different ridesharing scenarios without distinguishing drivers and passengers. We can see that solo drivers bear the highest environmental cost, increasing with trip distance. As more and more passengers start sharing the ride, the cost per person drops proportionally. Driving is, in general, much less environmentally friendly than taking trains. A road trip would cost a solo driver up to 56 € for the longest route in our sample, while the train environmental costs largely depend on the train type. Even for the least environmentally friendly mode (usually regional trains), it would only cost 1.47 € per person. On average, the socio-environmental cost of trains is 11% of the cost of a person who rideshares in a full car.

Table 4.14: Socio-Environmental Costs for Different User Profiles of All 396 Routes (in €)

	Min	Max	Mean	SD	P25	P50	P75
Solo Driver	3.79	56.52	10.58	7.34	6.34	8.82	12.69
Ridesharing with 1 Passenger	1.89	28.26	5.29	3.67	3.17	4.41	6.34
Ridesharing with 2 Passengers	1.26	18.84	3.53	2.45	2.11	2.94	4.23
Ridesharing with 3 Passengers	.95	14.13	2.64	1.84	1.59	2.21	3.17
Train passenger	.01	1.47	.13	.17	.06	.1	.15

[31] https://www.ecologique-solidaire.gouv.fr/sites/default/files/prix-carbone_4p_DEF_Fr.pdf, page 2.

[32] If the driver shares the ride also with passengers who do not book on BlaBlaCar website, for example, her family members, the calculation of environmental cost per person is incorrect. However, we ignore these scenarios.

To deepen this analysis, we conduct the following thought experiment. Suppose a train that should have carried 100 passengers is canceled, a social planner arranges or forces 25 passengers, each of whom own a car, to become BlaBlaCar drivers, and the remaining 75 passengers to share their rides. This hypothetical change of transport mode leads to 25 additional cars on the road. As the cancellation is irrecoverable, the choice does not depend on any information about the train.[33] We further assume that there is no other option than ridesharing on BlaBlaCar, and the objective of the commute is to go to work. If they cannot arrive at their destinations, they will be idle at home. Therefore, the social planner does not consider the time cost but the economic benefit of successfully arriving at the destinations. As the monetary exchanges on BlaBlaCar are zero-sum to society, the social cost is equal to the socio-environmental cost:

$$\Delta \mathrm{SC} = 25 \times E_r \tag{4.15}$$

where E_r is the socio-environmental cost of one additional car on the road. On the other hand, as the train option is no longer available and thus the loss of consumer surplus of taking a train is irrecoverable and not taken into consideration, the change in the social surplus of passengers is simply the sum of consumer surplus and producer surplus of ridesharing:

$$\Delta \mathrm{SS} = 75 \times \mathrm{CS} + 25 \times \mathrm{PS}, \tag{4.16}$$

assuming the driver's disutility of driving is exactly canceled out by the benefit of arriving at the destination. From the section of consumer surplus estimation above, we obtain the average consumer surplus per seat of a route (based on the information for non-strike days) as

$$\mathrm{CS} = \frac{\sum_t \mathrm{CS}_t}{\sum_t \overline{Q}_t} \tag{4.17}$$

and the producer surplus per driver of a route as

$$\mathrm{PS} = 3 \times P_{\mathrm{ref}} - f - \tau. \tag{4.18}$$

[33]We compare the welfare impact between "forcing 25 more cars on the road" and "leaving 100 passengers idle", but not between "canceling the train and forcing 25 more cars on the road" and "not canceling the train".

Thus the increase in the social welfare compared to leaving 100 passengers idle is:

$$\Delta W = \Delta \mathrm{SS} - \Delta \mathrm{SC}. \tag{4.19}$$

Figure 4.14 visualizes the increase in socio-environmental costs and the increase in the social surplus of moving 100 passengers from a canceled train to 25 cars for different route distances. The calculations follow Equations 4.16 to 4.19. The blue dots show the linear relationship between the socio-environmental cost and route distance. The black dots are the changes in the social surplus of 396 routes. For smaller distances below 250 km, many of the increases in social surplus are greater than the increase in socio-environmental cost, implying the hypothetical switch to BlaBlaCar would raise social welfare. However, as the distance increases, the hypothetical move would lead to lower social welfare.

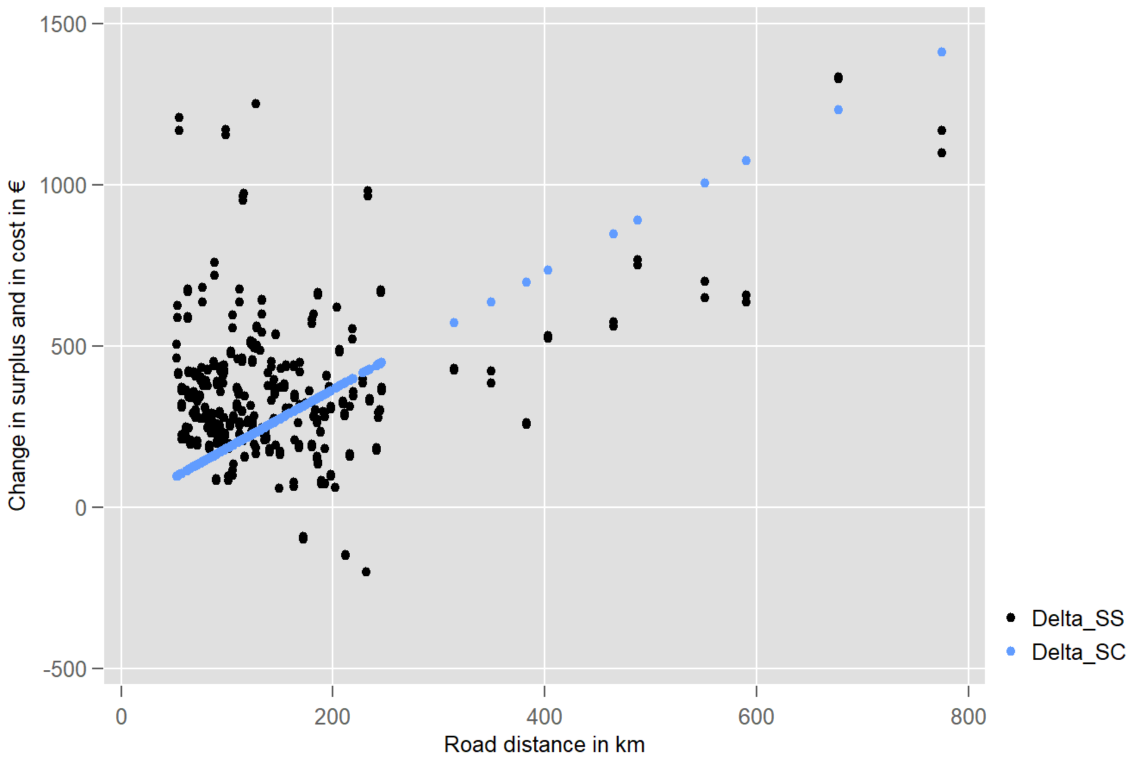


Figure 4.14: Comparison of Social Surplus and Social Cost of Switching 100 Passengers from Train to Ridesharing

The results from the above thought experiment is also in line with the individual choices. Recall from Figure 4.13, driving would also become more costly than taking trains when distance goes beyond 250 km. Under 250 km, driving, especially sharing the ride with others, is quite cost-competitive for many routes. This result has at least two implications. Firstly, ridesharing has the potential to improve welfare even taking into account the environmental costs, especially when the train, a widely-accepted environmental-friendly mass-transit system, is for some reason, not an option. Secondly, ridesharing is an attractive mode of transport, both from the social and individual perspectives, for relatively short distance travel (below 250 km).

4.10 Discussion and Conclusion

Strikes in public transportation systems limit people's mobility options, oblige them to adjust, and reorganize their trips, which will further distort economic activities related to those trips and generate extra costs for society. These strikes force people to consider switching to other modes and itineraries other than their usual ones. At the individual level, people may find that the initial routine is inferior to the new one (Larcom et al., 2017). For other business stake-holders in the sector, the temporary suspension of a competitor's services leaves them the space to develop. This work examines the economic impacts of the 2018 SNCF strike (the railway monopoly in France) on the inter-city ridesharing sector. The strike lasted for three months from April to June 2018 for every two out of five days. The calendar of the strike was announced to the public two weeks before the strike began. The random variation of the strike and non-strike days allows us to rule out the possibility that the strike days were selected based on some unknown confounding factors, such as day of the week or national holidays. This work also benefits from the rich data of BlaBlaCar, the largest inter-city ridesharing platform in France, via its public API.

Our work shows that during the strike period, on average, the number of seats offered by drivers increased by 7% on a strike day compared to a non-strike day. The effect on demand is more marked than supply. 29% more seats were booked on a strike day compared to a non-strike day. We then attempt to measure the consumer surplus generated by BlaBlaCar. For the initial 78 routes between major French cities that we collected information from the official API, BlaBlaCar generated on average 39,045 € on a non-strike day and an additional 7,846 € consumer surplus on a strike day. To give a more general perspective for the whole of France, we then expand the sample to include more routes between smaller and neighboring cities. By propensity score matching, we matched consumer surplus estimates to the newly selected 318 routes and the 396 routes as a whole generated 79,413 € on an average non-strike day and an additional 17,753 € on a strike day.

Our results support a causal effect of the SNCF strike on the significant increases in the supply and demand of inter-city ridesharing, suggesting that ridesharing could be a useful substitute during the suspension of railway services. We further take into account the time and other financial costs in the individual choice of transport for each of the 396 routes. Ridesharing shows excellent potential for reducing personal costs, especially for trips shorter than 250km. Traveling by trains only catches up with ridesharing with three passengers when the distance is sufficiently long. Moreover, we conduct a thought experiment of moving 100 train passengers to ridesharing and verify if that move would improve social welfare by taking into account the socio-environmental costs of car emissions. For routes shorter than 250km, ridesharing could be socially beneficial, while trains are more efficient when the distance is longer than 250km. This result is consistent with the individual choice analysis; ridesharing tends to be a cost-saving option for shorter distances.

Our research is, however, not without limitations. We only possess the information of the strike period (April to June) and another month after the strike (July), meaning that any estimates concerning those strike days may not apply to a hypothetical strike day in other months. The period was a volatile period for the transportation sector as people could make up canceled trips on other days, causing the demand and supply to deviate from an actual average day. On the other hand, as no equivalent data on SNCF are available, we cannot complete a comprehensive comparison of the social surplus.

Our research has several policy implications. Firstly, it measures the impact of a significant industrial action, the 2018 French railway strike, on the inter-city ridesharing. The supply, demand and welfare calculations help policymakers understand the scale of the impact and the extent of substitution between the two types of services. Secondly, our work demonstrates the benefit of a ridesharing practice. Ridesharing has been developing rapidly in recent years due to the booming digital economy and public policy support, and BlaBlaCar is the leader of the ridesharing market with 70 million registered users in 22 countries in 2019. This work evaluates the impact of this growing industry. Previous research discussing the potential benefits of ridesharing focused on its merits to reduce pollution and congestion, while our work gives insights to the position of ridesharing as a viable transportation solution. Our work shows that ridesharing platforms help adjust the supply and absorb additional the demand with flexibility, while the overall costs are lower than taking trains for short distance travels and roughly similar for longer distances if sharing with three passengers.

We suggest policymakers integrate ridesharing, as well as other flexible mobility modes, in the conception of transportation systems, especially for remote areas where trains and other public transportation modes are insufficient. Private businesses have already started this movement, and SNCF has been collaborating with three ridesharing platforms since 2018. People who search for train itineraries on its website can also compare ridesharing offers at the same time. SNCF had wished to cancel several loss-making train lines in remote cities, but the plan did not eventually pass because of the concerns that the residents would not have sufficient transportation solutions. Had ridesharing been fully developed, the suppression or reduction of such train lines could have been cost-effective and welcomed by the residents.[34]

[34]For the press reference, see https://www.lefigaro.fr/vox/societe/2018/02/28/31003-20180228ARTFIG00143-fermeture-de-lignes-sncf-un-pas-de-plus-vers-la-desertification-rurale.php.

CONCLUSION

Ridesharing is an innovative mobility mode as it brings together different concepts such as digital platforms, the sharing economy, and transportation operations. As a consequence, it raises intense academic research interest. However, at the current stage, due to the lack of data availability, our understanding of ridesharing remains limited. In the thesis, we review the current knowledge of ridesharing, especially the various business models in the French market. We then deepen the understanding of ridesharing in two aspects. Firstly, we focus on the individual motivations and point out the role of prosocial motivations in short-distance rural ridesharing. Secondly, we focus on the substitution effects of ridesharing and train commuting to evaluate the social impact of ridesharing. Both aspects help to promote a ridesharing service that motivates participation and benefits the society, and thus could be sustainable.

We study motivations by conducting field experiments as this allows motivations to be revealed in real settings. Duflo and Banerjee (2017) give a detailed review of the advantages and methodological challenges of field experiments. The first two experiments are constrained by the field conditions and are limited in scale compared to more complex field experiments. The results of the second experiment may lack statistical power and need to be supplemented by other experiments. There may be other unknown biases that may affect the impact, and are subject to the main criticisms of field experiments such as external validity and spillover effects. Despite these limitations, we begin to the understand the individual motivations of users to participate in ridesharing. The two exploratory studies fill in the literature blank in this emerging sector.

The third research mainly focuses on the monetary impacts of a railway strike on ridesharing, though we add a preliminary welfare analysis that takes into account other externalities. It is preliminary because the proposed method to estimate the consumer surplus has potential for methodological improvements and because we could not exhaustively collect all the rideshares from the ridesharing platform to give a complete estimation of the impact of the strike.

Moreover, some of these limitations provide impetus for some future directions for research. For business-level incentives, we would like to carry out more experiments on user motivations under a wider variety of settings, as monetary and prosocial motivations may interact differently to the cases that we have explored. For example, we have found some evidence that monetary incentives may be a necessary element for drivers who rideshare regularly. This leads to many follow-up questions. If money becomes a “must have” for regular drivers, how much should we compensate them? What would be the impact of other non-monetary motivations, especially solidarity motivations? For passengers, once there is a pool of regular drivers, would their perception of uncertainty change? What would be effective ways to overcome their psychological barriers? These questions become even more important to answer as ridesharing gains more popularity.

We would also like to run a deeper analysis of the impact of the strike on the transportation sector. With the existing data which includes one month after the strike, we can envisage examining if the external shock leads to trends of habit formation. If we collect more complete data of the trains, coaches, and other complementary modes, then we could extend the analysis to the entire sector.

Since the 2018 national railway strike, there have been other significant external shocks that have profoundly influenced people's daily travel routines. Since autumn 2019, there have been ongoing public transportation strikes in protest against the French government's proposed reforms of retirement pensions. In December 2019, the public transportation service in the entire Paris region is heavily reduced, and in some cases to zero, for several weeks. For inter-city travel, SNCF also participates in the strike, although at a much smaller scale compared to the 2018 strike. During this period, ridesharing companies, especially those focused on urban work commutes, actively promote their services. It would be interesting to investigate the changes in travel behavior and the likelihood of habit formation after the extended strike. The main difficulty of such research is the data availability since the multiple ridesharing stake-holders have not yet demonstrated their intentions to share their data.

From March 2020, the Covid-19 crisis hits France. Under the wide-reaching lockdown, residents are constrained to limit unnecessary travel and contact with other people. Ridesharing, as it is based on human contact, becomes extremely vulnerable compared to other mobility solutions as solo driving becomes the safest mode. Once this lockdown is lifted (it is still in place at the time of writing), research could be carried out to investigate whether this health crisis has a lasting impact on the perception of ridesharing and on the habit of mobility.

This thesis marks only a beginning in the application of multiple empirical methodologies to understand ridesharing. We suggest that researchers join in the analysis of this growing sector and that service providers open up more research collaboration opportunities.

APPENDIX A

APPENDICES OF CHAPTER 2

A.1 Demonstration of A Ridesharing Station for Experiment 1

Demonstration of one of the ridesharing stations where the experiment takes place. The green pillar is where passengers should log in and buy tickets. Passengers should then wait close to the station to be easily found by drivers.

A.2 Demonstration of An LED Screen for Experiment 1

Demonstration of a LED screen with a ridesharing request displayed in real time. It shows the number of passengers, as well as the requested destination. The destination is masked for confidentiality. Drivers can not see the price level of the trip in the experiment.

A.3 Passenger's Guide

covoit ici | Le service public de covoiturage quotidien pour tous

Guide de participation
Programme d'amélioration

Ce guide vise à vous rappeler les points essentiels de votre participation et clarifier le comportement à adopter. Les consignes fournies ici sont absolument essentielles pour que les données des trajets soient valables et que vous puissiez être indemnisé en conséquence.

Quelques rappels sur le programme

Vous devez réaliser **au moins 2 trajets par semaine sur la période de 4 semaines entre le 9 janvier au 5 février 2017.** Nous vous encourageons à en réaliser plus si vous le pouvez.

Vous êtes libres de choisir les jours et horaires pour voyager à votre convenance. Nous vous contacterons à la fin de chaque semaine pour connaître votre planning approximatif des trajets de la semaine suivante.

Ce programme d'amélioration se concentre sur le Val d'Oise, en particulier au départ de la station de Chars ; mais nous pouvons également inclure des trajets au départ des stations de Marines, Osny et Magny-en-Vexin.

Les trajets en covoiturage sont gratuits pour vous, pris en charge par le service.
Pour chaque trajet accepté par le service, effectué en respectant le fonctionnement normal et pour lequel le questionnaire a bien été rempli, vous serez indemnisé de 5 € sur votre compte COVOIT'ICI.

Déroulement d'un trajet type

- Rendez-vous à la station COVOIT'ICI et faites votre demande de covoiturage à la borne **À la différence d'un trajet normal, il vous est demandé de sélectionner une destination précédée par « Le ». Par exemple, pour aller à Cergy, sélectionner « Le Cergy »**
- Restez près de la borne de covoiturage de manière visible
- Renouveler l'affichage de votre demande sur la borne toutes les 10 minutes
- Ne quittez pas la station avec une demande en cours. Si vous devez vous absenter, annulez votre demande
- Lorsque qu'un conducteur s'arrête, validez le trajet à la borne avant de monter. En cas d'oubli, merci de remplir sur le questionnaire l'heure exacte de montée
- Comportez vous naturellement lors du trajet, comme n'importe quel passager
- **Ne mentionnez pas que vous êtes en test et ne divulguez pas d'information sur le programme d'amélioration.** Pour que nous puissions utiliser les données de vos trajets, ceci est absolument indispensable.
- Observez la voiture, le (la) conducteur (conductrice), estimez leur âge, sexe, comptez le nombre de places libres et le nombre d'enfants dans la voiture. Cela vous permettra de répondre à la première partie du questionnaire.

- De manière naturelle, interrogez votre conducteur sur le motif de son trajet, s'il connaît COVOIT'ICI ou non, s'il a déjà pris un passager avant
- Avant l'arrivée, transmettez le ticket au conducteur et expliquez lui le principe du partage des frais
- Indiquez qu'ils peuvent se rendre sur covoitici.fr pour encaisser l'argent (c'est marqué sur le ticket)
- Précisez bien que peu importe si le conducteur encaisse ou non, vous avez déjà payé et ne pouvait pas être remboursé
- Si le conducteur le refuse tout d'abord, déposez le simplement sur votre siège en leur rappelant que c'est à eux de faire le choix de ce qu'ils font du ticket
- Une fois débarqué par votre conducteur, vous remplissez le questionnaire en ligne sur **ecov.typeform.com/to/eEOJx1**

Quelques précisions sur le comportement à bord du véhicule

Lors de ces trajets, vous êtes déterminant dans l'expérience que le conducteur aura du service. **Merci donc de vous comporter avec courtoisie.**

Pendant le trajet, vous êtes libre d'échanger avec le conducteur, mais vous devrez au moins poser les questions suivantes :
- Si le conducteur connaît le service (en a entendu parlé, connaît le fonctionnement etc)
- Si le conducteur a déjà pris un passager avant
- Si aujourd'hui il fait un trajet régulier, et pour quel motif (domicile-travail, courses, etc.).

Un exemple : ***« Merci de vous être arrêté ! Vous avez vu le panneau lumineux pour vous arrêter ? »*** Si oui, vous pouvez ensuite poser la question : ***« Ah, vous connaissez COVOIT'ICI alors ! »*** et à cette étape-là, les conducteurs vont normalement raconter leurs expériences avant s'il y en a. Pour demander le but du trajet, au lieu de le demander directement, vous pouvez d'abord lui préciser où voulez-vous aller, puis leur demander ***« Ça ne ferait pas trop de détours pour vous ? Êtes-vous pressé ? Allez-vous au travail ? Vous faîtes ce trajet tous les jours ? »*** etc.

Attention : Si le conducteur a déjà pris un passager COVOIT'ICI, demandez-lui s'il a participé récemment pour savoir si c'était pendant la période du programme. Si oui, rappelez-vous de ce que le conducteur vous dit et retranscrivez-le dans la dernière question du questionnaire (question ouverte).

Questions-réponses

Si le conducteur s'interroge sur le montant du ticket ou le trouve plus élevé qu'à la normale, répondez que vous avez payé comme d'habitude, que c'est peut-être le service qui a augmenté la rémunération des conducteurs.
Si le conducteur vous demande si l'augmentation de prix est devenue une nouvelle fonctionnalité du service, répondez que vous ne savez pas.

Le mot de la fin

À tout moment, avant, pendant ou après votre covoiturage vous pouvez contacter le service COVOIT'ICI au 01 79 73 89 73.

En cas de difficulté avec le questionnaire en ligne ou avec ce guide, contactez directement Diane au 06 61 31 15 52.

Ce guide contient beaucoup d'information mais après une première fois, vous verrez que ce n'est pas compliqué et que l'ensemble se déroule naturellement. N'hésitez pas à nous contacter pour que nous vous accompagnions lors de votre premier trajet.

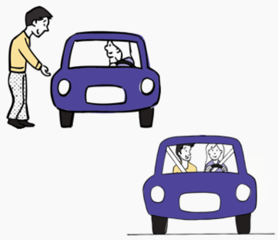
Comment ça marche ?

ETAPE 1

Le conducteur se déplace comme d'habitude
A la station de covoiturage le passager se connecte (ou s'inscrit) sur la borne.
Il rentre sa destination. Le temps d'attente estimé et le prix pour cette destination sont indiqués.
Il valide, paye, et récupère son ticket.

ETAPE 2

Sa destination est instantanément affichée sur les panneaux lumineux de la station de covoiturage, visibles de tous les conducteurs passant devant.
Ainsi informé, un conducteur s'arrête.

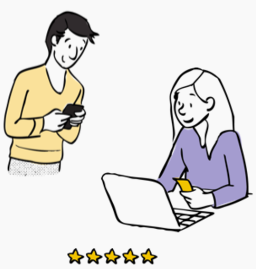


ETAPE 3

S'il veut, avant de monter, il peut envoyer la plaque d'immatriculation par SMS à un numéro dédié.

ETAPE 4

S'il veut, le conducteur peut demander au passager son ticket pour le vérifier, et pour envoyer le code y figurant par SMS à un numéro dédié. Ceci lui permet de signaler qu'ils vont covoiturer ensemble.
Ils covoiturent.
Le passager donne son ticket au conducteur.



ETAPE 5

Passager bien arrivé. Il peut noter son conducteur s'il le souhaite.
Le conducteur récupère l'argent sur internet grâce au ticket, dans les 14 jours qui suivent le covoiturage.
Il peut noter son passager.

A.4 Questionnaire for Experiment 1 for Hired Passengers (Translated into English)

1 → Votre nom :* Your name

2 → Code du ticket* Ticket code

En cas d'oubli, merci de noter la station de départ ainsi que la date et heure

3 → Heure de départ (optionnnel) Time of departure (optional)

Impératif si vous n'avez pas signalé votre départ.

4 → Marque de la voiture (optionnel) : Brand of the car (optional)

Laissez ce champs vide si vous n'êtez pas sûr.

5 → Âge du conducteur :* Estimated age of the driver

A 18-30 | B 30-45 | C 45-60 | D 60+

6 → Sexe du conducteur :* Gender of the driver

A Femme | B Homme

7 → Nombre de sièges vides disponibles dans la voiture :* Number of empty seats in the car

En incluant celui que vous occupiez.
Ex: 1 conducteur seul dans une voiture 5 places a 4 sièges vides.

8 → Nombre d'enfants dans la voiture : Number of children in the car

9 → Le conducteur connaissait-il le service ?* Did the driver know the service (when he stopped)?

A oui, en avait entendu parlé | B oui, savait comment ça marche | C non, ne conaissait pas

A. Yes, had heard of it
B. Yes, knew how it works
C. No, didn't know

10 → Le conducteur avait-il déjà pris un passager COVOIT'ICI auparavant ?*

Has the driver already picked up a passenger before?

A oui | B non

11 → Étais-ce un trajet ...*

Is it a routinely trip or an occasional one?

- A régulier
- B irrégulier

12 → Motif du trajet :

Purpose of the trip (home-work, leisure, administrative/health, other)

- A Domicile-travail ou domicile-études
- B Loisirs
- C Administratif/santé
- D Autre

13 → Météo :*

Weather (good, cloudy, rainy/snowy/misty)

lors de l'arrêt de votre conducteur à la station COVOIT'ICI

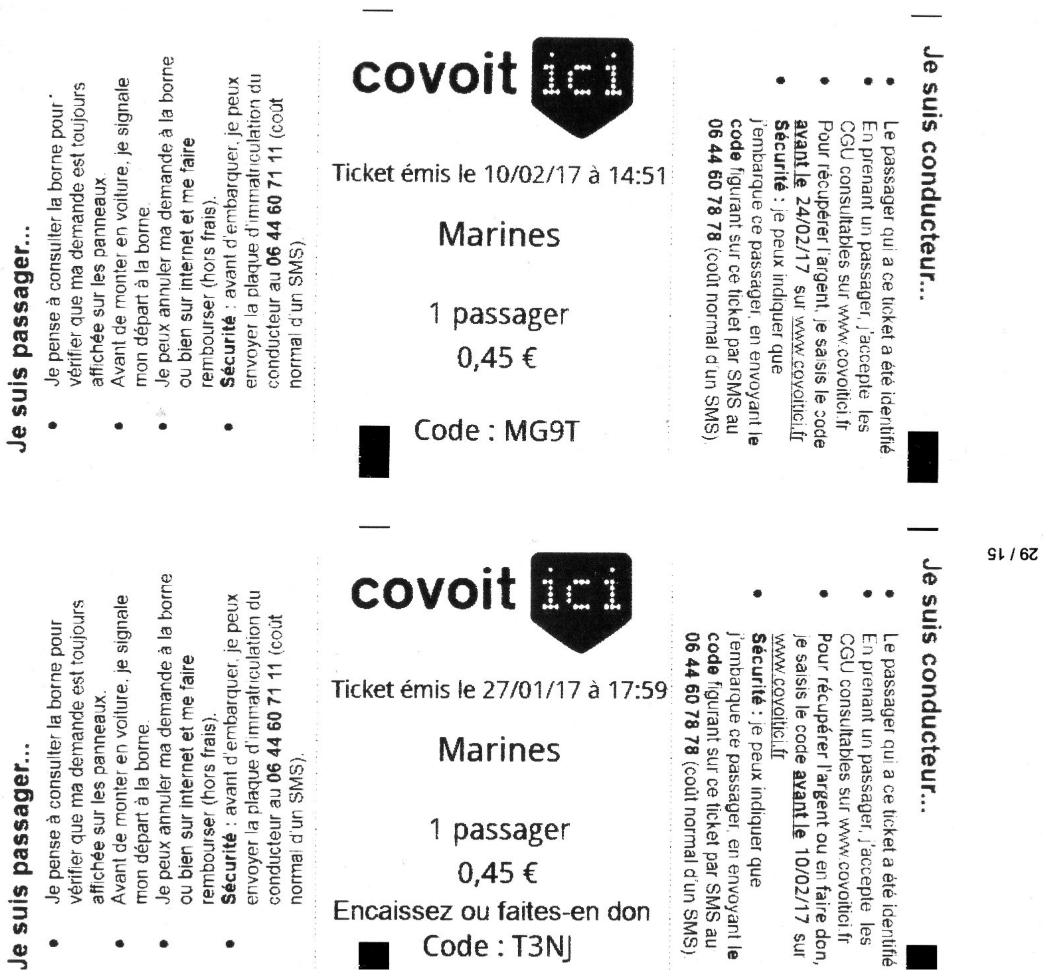
- A beau temps
- B nuageux
- C pluie, neige, brouillard

14 → Vos remarques :

Remarks/notes

Partagez ici toute information qui n'aurait pas été capturé dans les questions précédentes.

A.5 Tickets of Experiment 1 With and Without Donation



Je suis passager...

- Je pense à consulter la borne pour vérifier que ma demande est toujours affichée sur les panneaux.
- Avant de monter en voiture, je signale mon départ à la borne.
- Je peux annuler ma demande à la borne ou bien sur **internet et me faire** rembourser (hors frais).
- **Sécurité** : avant d'embarquer, je peux envoyer la plaque d'immatriculation du conducteur au **06 44 60 71 11** (coût normal d'un SMS).

covoit ici

Ticket émis le 10/02/17 à 14:51

Marines

1 passager

0,45 €

Code : MG9T

Je suis conducteur...

- Le passager qui a ce ticket a été identifié
- En prenant un passager, j'accepte les CGU consultables sur www.covoitici.fr
- **Pour récupérer l'argent**, je saisis le code **avant le** 24/02/17 sur www.covoitici.fr
- **Sécurité** : je peux indiquer que j'embarque ce passager, en envoyant **le code** figurant sur ce ticket par SMS au **06 44 60 78 78** (coût normal d'un SMS).

Je suis passager...

- Je pense à consulter la borne pour vérifier que ma demande est toujours affichée sur les panneaux.
- Avant de monter en voiture, je signale mon départ à la borne.
- Je peux annuler ma demande à la borne ou bien sur **internet et me faire** rembourser (hors frais).
- **Sécurité** : avant d'embarquer, je peux envoyer la plaque d'immatriculation du conducteur au **06 44 60 71 11** (coût normal d'un SMS).

covoit ici

Ticket émis le 27/01/17 à 17:59

Marines

1 passager

0,45 €

Encaissez ou faites-en don

Code : T3NJ

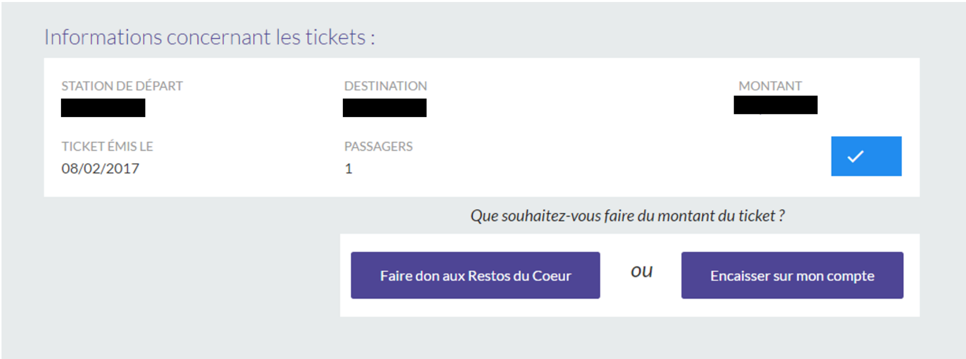
Je suis conducteur...

- Le passager qui a ce ticket a été identifié
- En prenant un passager, j'accepte les CGU consultables sur www.covoitici.fr
- **Pour récupérer l'argent** ou en **faire don**, je saisis le code **avant le** 10/02/17 sur www.covoitici.fr
- **Sécurité** : je peux indiquer que j'embarque ce passager, en envoyant **le code** figurant sur ce ticket par SMS au **06 44 60 78 78** (coût normal d'un SMS).

29 / 15

Demonstration of two tickets for short-distance trips used during the experiment. The name of the destination is anonymized by "destination". The first ticket is without the donation option, and the second is with the donation option. The only difference is that the second ticket has one more phrase between "0.45€" and the code of the ticket, indicating that the driver can "cash out or donate the money (mentioned above)". The tickets also contain information on the number of passengers of the trip, the time of the request, and practical information for passengers and drivers. Tickets for long-distance trips are the same in terms of design, except that the date and time, the destination and the price change accordingly.

A.6 Demonstration of the Donation Process for Experiment 1



Screenshot of the donation page that appears after entering the ticket code. During the weeks where the donation option is activated, drivers face the choice between cashing out the amount or donating the amount to *Restos du Coeur*, a French charity food bank. They can only choose one option, and the choice applies to the entire amount of the ticket.

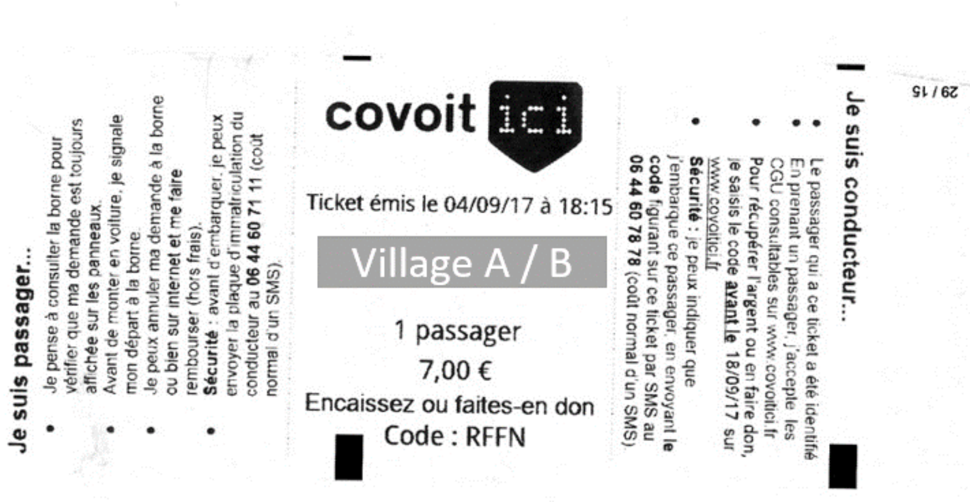
APPENDIX B

APPENDICES OF CHAPTER 3

B.1 Demonstration of A Ridesharing Station for Experiment 2

Illustration of a ridesharing station in Experiment 2. A typical station is composed of a ticket machine (in green and yellow), a small solar-powered information screen which can also show a short version of request, a dedicated parking space, and some auxiliary decorations.

B.2 Ticket for Experiment 2

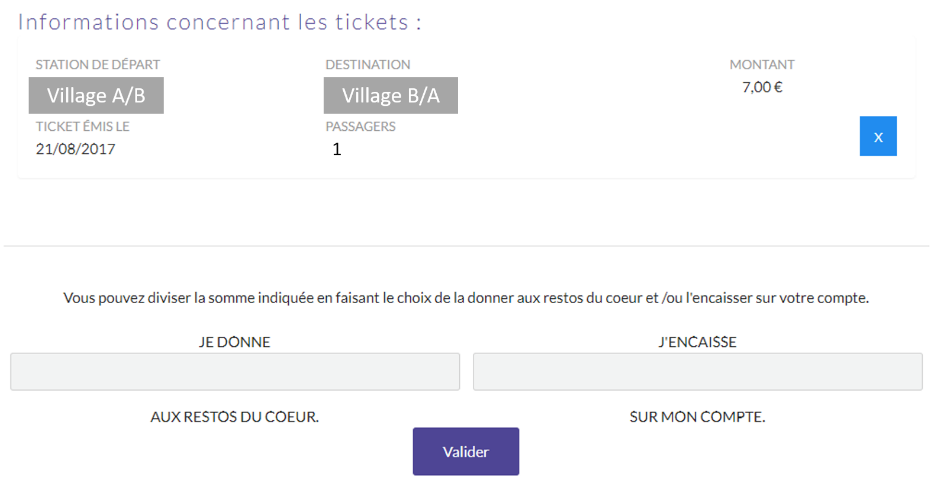


Example of a ticket that drivers would see during the experimental period. Essential information of the trip is in the central part of the ticket: date, destination (anonymized here), code (needed for cashing out or donation), compensation level, and the possibility to donate (*"Encaissez ou faites-en don"*). On the left and right sides of the ticket is practical information for passengers (on the left) and drivers (on the right). Tickets of 3 euros look the same as tickets of 7 euros, except for the compensation.

B.3 Message Shown on the Screen for Experiment 2

Demonstration of the message shown on the information screen. The name of the village is anonymized. *EMMENEZ 1 PASSAGER A [village A/B], GAGNEZ 7 €* in French means "Take a passenger to village A (or B) and gain 7 euros". Message of 3 euros tickets looks the same as this one, except for the compensation.

B.4 Money Split Webpage for Experiment 2



Screenshot of the ticket cash out and donation page. This page will appear once drivers enter the code of the ticket. The upper part of the web page shows some basic information about the trip (departure, destination, date, passenger number, compensation level). The lower part of the web tells drivers that they can split their compensation between their account and the charity *Les Restos du cœur*. Drivers then need to enter precise amounts in each blank (left side for the charity and right side for their account) before validating. If amounts in the two blanks do not sum up to the compensation amount, validation is not accepted.

B.5 Questionnaire for Experiment 2 for Hired Passengers (Translated into English)

1 Your name : *

2 4-digit code printed on your ticket: *

3 Number of cars passing by towards the right direction before someone picked you up: *

4 Brand of the driver's car (leave it blank if you are not sure):

5 Approximate age of the driver: *

- 18-30
- 30-45
- 45-60
- 60+

6 Gender of the driver (if several people were in a car, please reply with the gender of the person who was driving): *

- Female
- Male

7 How many available seats were there in the car before you got on (excluding baby seats)? *

8 Number of children in the car:

9 Did the driver see the screen and the compensation level? *

- Yes, he/she saw both
- He/she saw the screen but did not pay attention to the compensation level
- No, he/she did not see the screen

10 Did the driver know the service (Covoit'ici) before picking you up? *

- Yes, has heard about it
- Yes, knew how it works
- Yes, has registered on the website
- No, didn't know

11 Has the driver picked passengers up before using the product? *

- Yes
- No
- I don't know

12 If yes, was it during the experiment period (June and July 2017)?

- Yes
- No
- I don't know

13 It's a... *

- Regular trip (several times a week)
- Irregular/occasional trip

14 Please note down regular trips of the driver (if mentioned):

Example: Each week day at 8 a.m. from village A to village B

15 What's the driver's general impression of ridesharing? *

- Positive
- Neutral
- Negative
- Not clear/with doubts
- Didn't talk about it

16 What are the motivating factors mentioned by the driver for picking up passengers? *

Multiple choices possible

- To gain money, to reimburse fuel costs, etc.
- To socialize with people
- It's convenient to stop/It's on the way
- To help people out and to show support
- To protect the environment
- Other (please specify)
- We didn't talk about it

17 Could you note down some of the driver's narration to support your choice on motivations?

18 How did the driver react when he/she leant that it was possible to cash out partial or entire amount of the compensation printed on the ticket? *

Multiple choices possible

- Rather negative/Didn't want to get paid
- More or less neutral/Didn't react
- Rather positive
- He/she thought that the compensation level was high
- He/she thought that the compensation level was OK/Didn't react to compensation level
- He/she thought that the compensation level was low
- Other (please specify)

19
How did your driver react when he/she leant that it was possible to donate partial or entire amount of the compensation to charity?
*

- He/she was enthusiast
- He/she was so enthusiast that he/she even planned to donate
- He/she was neutral/didn't react specifically
- Other (please specify)

20 Weather during the waiting periode : *

- Nice weather
- Cloudy
- Rainy/greasy

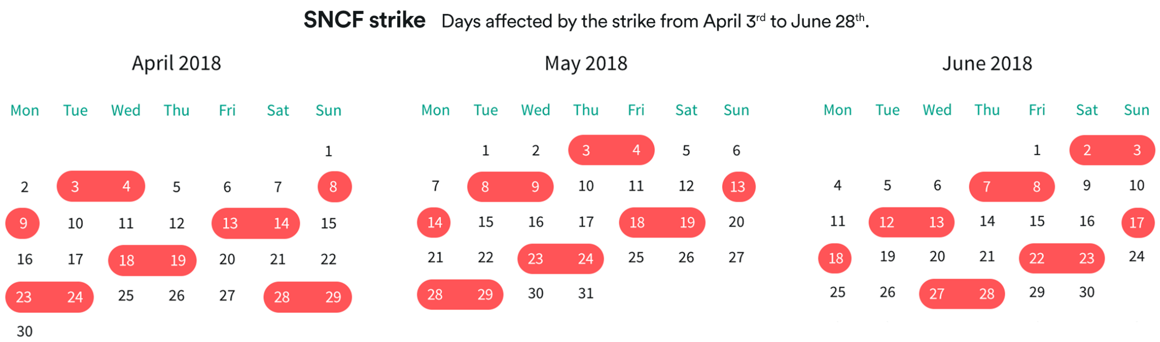
21 Other comments:

Send response

APPENDIX C

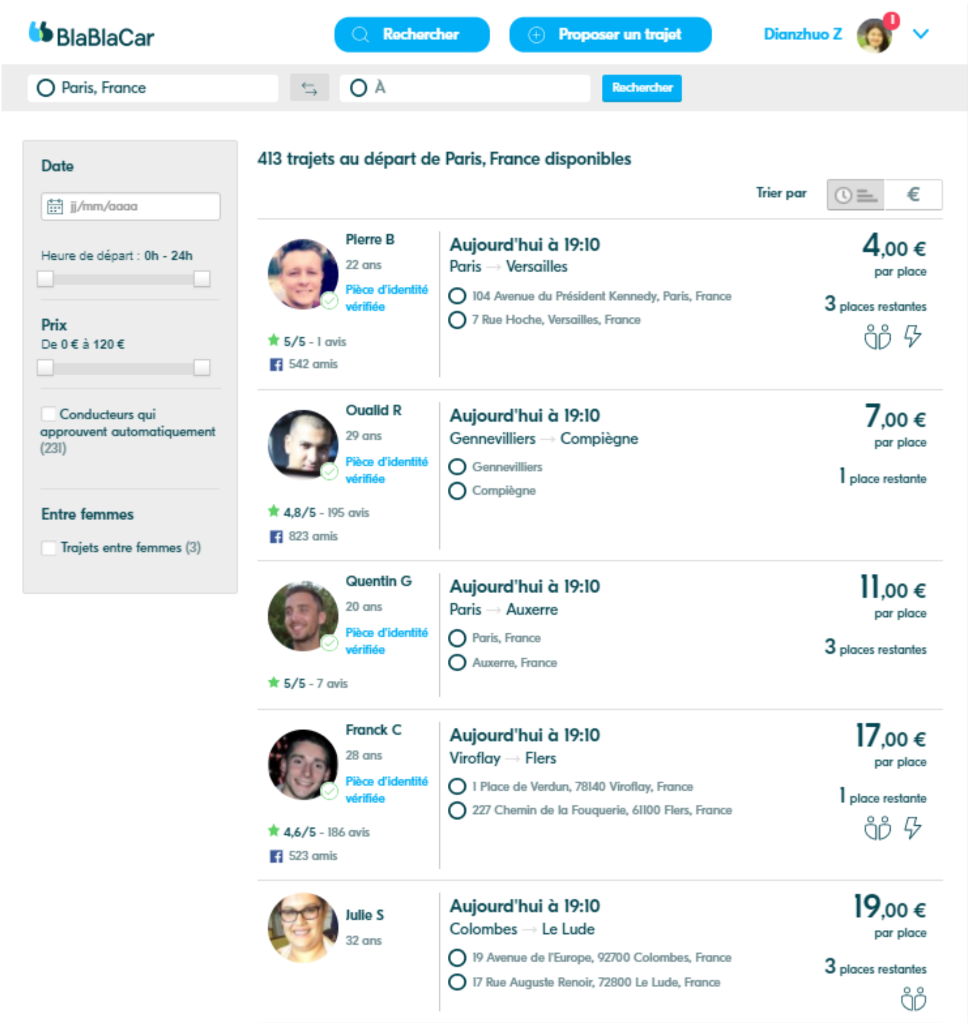
APPENDICES OF CHAPTER 4

C.1 SNCF Strike Calendar

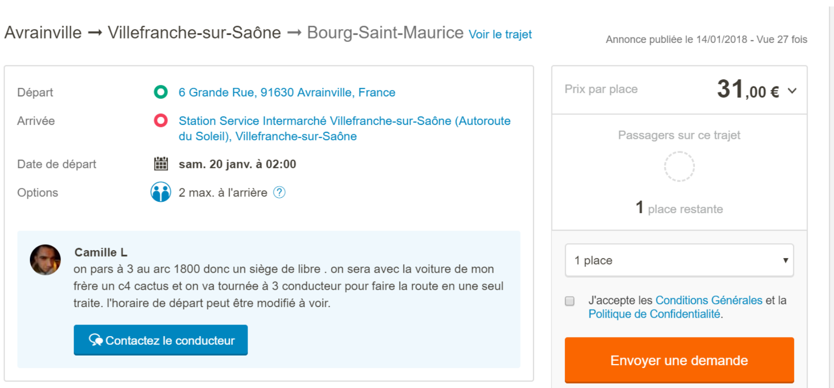


Strike dates are marked in red. Retrieved in January 2019 from https://faq.trainline.eu/article/674-sncf-french-rail-strikes-2018.

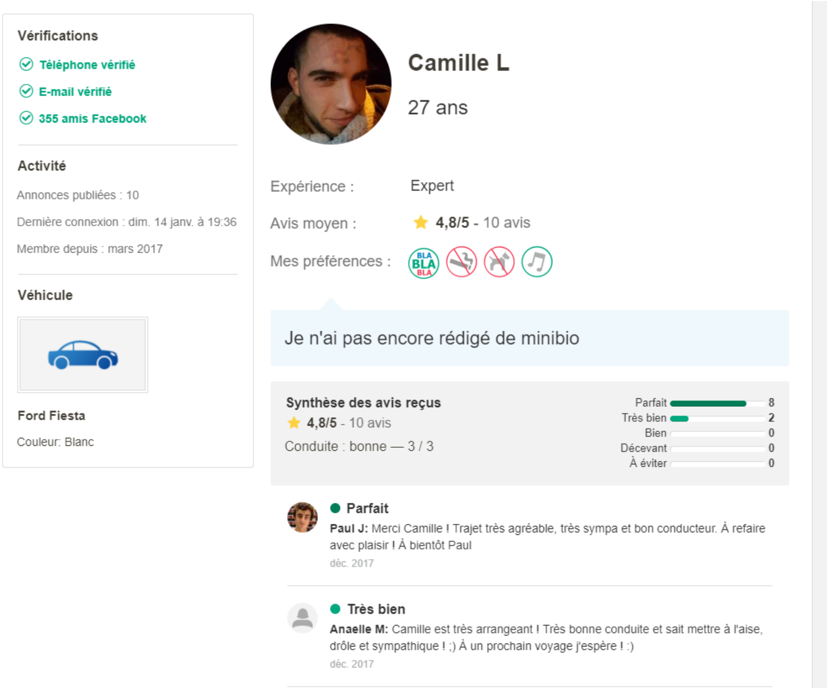
C.2 BlaBlaCar Trip Search Pages



Demonstration of the trip search results. Retrieved in 2018 from BlaBlaCar.fr. The web page design changed in summer 2018 after our analysis period.

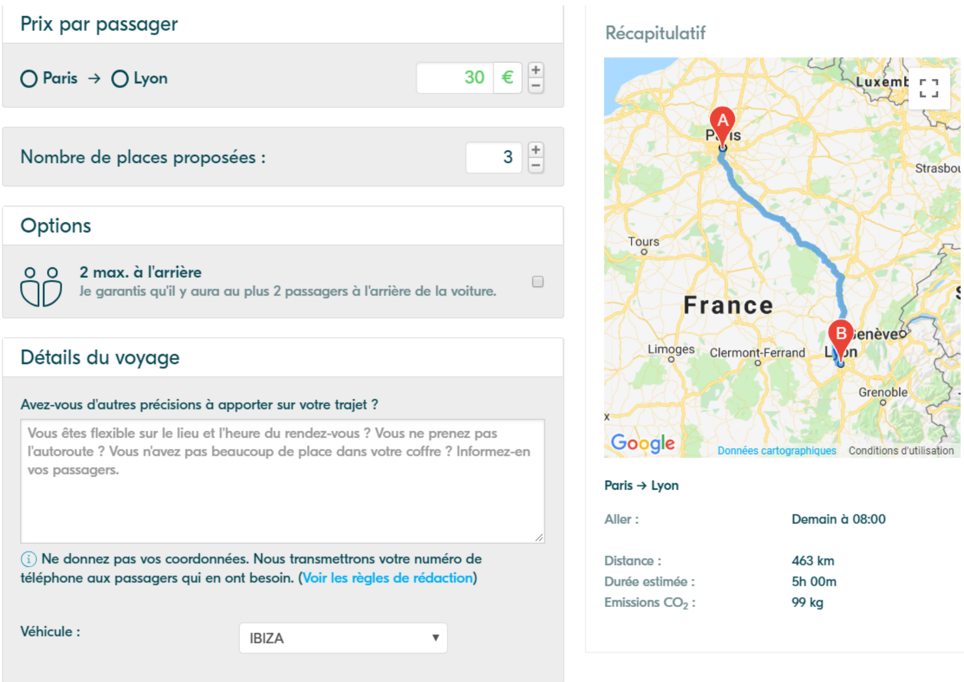


Demonstration of the trip information page. Retrieved from BlaBlaCar.fr in 2018. All information was publicly available.



Demonstration of the driver information page. Retrieved from BlaBlaCar.fr in 2018. All information was publicly available.

C.3 BlaBlaCar Route Default Price Simulation



Demonstration of the driver's process of trip publication using Paris-Lyon as an example. BlaBlaCar shows the default price after that the driver has entered the departure, destination, and timing of the trip.

C.4 BlaBlaCar Commission Levels

Table C.1: Commissions Charged by BlaBlaCar (in €)

Price charged by driver	Commission level
1-6	1.0
7-8	1.5
9-11	2.0
12-13	2.5
14-16	3.0
17-18	3.5
19-21	4.0
22-23	4.5
24-26	5.0
27-28	5.5
29-32	6.0
33-35	6.5
36-37	7.0
38-40	7.5
41-42	8.0
43-46	8.5
47-50	9.0
>51	18% of price, rounded to nearest 0.5€

Commission level does not change according to the routes, hours, or days. Information collected from https://blog.BlaBlaCar.fr/blablalife/lp/nouvelle-grille-de-frais-de-reservation in 2018. This page no longer exists since BlaBlaCar has changed their commission policy in 2019 with a slight increase. The new policy is explained here: https://www.BlaBlaCar.fr/faq/question/comment-sont-calcules-les-frais-de-reservation

C.5 BlaBlaCar API Data Collection and Cleaning Details

The data collection starts on April 1, 2018, two weeks after SNCF's announcement of a strike and two days before the strike starts (April 3). The scraping ends on August 3, 2018. We extend the collection period one month after the end of the strike to use the post-strike month as the control period.

From April 1 to August 3, we run the scraping program every day at the end of the day, typically from 18:00 to 19:00. The choice of retrieving the data each day is a balance of accuracy and convenience. Retrieving more than once per day will give a more complete sample and will track changes more precisely, but the incremental benefit does not compensate for the difficulty of maintaining a much larger dataset and the risk of exceeding the daily limit of API queries. Retrieving once every several days may result in losing track of significant changes that occur on a specific day and in confounding the cause of the change with the specific characteristics of the day, such as being on a strike date or not, being on a weekday or weekend. Since most of the trips depart before 7 p.m., retrieving at the end of the day increases the chance of capturing the end status of trips after departure and before being deleted.

For our analysis, we need only to keep the final observation of each trip, but we create additional variables to indicate changes. Instead of keeping 15 observations of trip that has three bookings in dates A, B, and C, it is enough to keep the last status of the trips and to add three more variables of "seat one (or two, or three) booked date". The same logic applies to the evolution in other variables. We first clean our data set in this way to reduce the data size significantly without losing important information.

Even though each data retrieval returns correct information of the trip at the moment of retrieval , these data from API could be biased in two ways. The first bias is that the trip information evolved after the latest retrieval , but the evolution failed to be traced because the trip had been deleted from the API before the next retrieval session. This failure would create a downward bias of the supply and demand estimation if drivers had put more seats available or that more passengers had booked seats in between the latest retrieval and deletion. An upward bias of supply and demand estimation would occur in the reverse cases.[1]

The second bias is that some drivers cancel their trips and cause them to be deleted from the API before departure.[2] However, we may interpret the case as that the trip has a full booking, creating an

[1]There may even be trips that are published, fully booked, and then deleted between two retrieval dates, that we are even not able to retrieve once. They will be considered as to have never existed, which makes our estimation of supply and demand downward biased. However, we ignore this bias in this paper because we have no way to verify its scope nor to correct it.

[2]We learned anecdotally from an experienced BlaBlaCar driver that driver cancellation is not uncommon. To maximize the chance of being booked, some drivers publish multiple listings at different schedules for the same

upward bias in actual supply and demand estimation. Even though we could not be sure of the final status of each trip, we could nevertheless apply some rules to minimize the bias. Three scenarios may happen.

Scenario 1: At day $N+1$, we still observe trips whose departure date is N. This is the ideal situation. We can take the offer and booking data of the latest retrieval day as the final status of the trip.

Scenario 2: The last time that a trip has a retrieved record is on the same day as its departure date. This situation is not ideal but still gives us confidence in the trustworthiness of the latest retrieval . Since usually retrieval takes place between 6 to 7 p.m. and lasts no more than one hour, trips departing before 8 p.m. that day could all be considered as finished when retrieval takes place so that scenario 1 applies. For trips departing after 8 p.m. but somehow can no longer be found the day after, we consider them as fully booked in the last minute and then were deleted from the API. We then adjust the booking data in our data set.[3]

Scenario 3: The last time that a trip has retrieved record is before its departure date. This is the most complex situation. Many possibilities apply, which makes it impossible to de-bias perfectly. We here apply a simple, straightforward but still efficient rule based on two rationales: Firstly, the earlier compared to the departure date the trip disappears from API, the more likely that the driver cancels it. Secondly, the fewer the booking records when the trip disappears from the API, the more likely that the driver cancels it, especially when the trip disappears without any bookings. Our rules of adjusting seats offered and booked are as follows:

If a trip has four and more unbooked seats before being deleted from the API, even if it happens only one day before departure, we assume that the driver has canceled it. If a trip has three unbooked seats before being deleted while only three seats are available for booking, we also assume that the driver has canceled the trip. However, if the total seat number goes beyond three while unbooked seat number is three, which means that the trip has been booked at least once before being deleted, we assume that it has a full booking. If a trip has only 1 or 2 unbooked seats before being deleted, we consider it as fully booked because it is relatively common to have one or two bookings coming in the last minute.

trip and cancel the unpopular ones once a proposed itinerary is booked. We have no information on how common the practice is among drivers. In terms of the platform policy, during the data collection period, drivers can cancel the trip at any time, even if the trip has bookings already. No penalty will be applied except that drivers who often cancel at the last minute may not be able to publish new trips.

[3] It is also possible that the driver canceled the trip in the last minute, but since it should be rare and not encouraged by the platform, we ignore this possibility here.

C.6 Information about Observed (API-collected) Routes

Table C.2: List of Observed Routes (One Way) and Reference Information

Route	Upper Price Limit	Lower Price Limit	Default Price	Distance (km)
Major to major cities				
Paris Lyon	37	13	29	469
Paris Marseille	62	22	49	775
Paris Bordeaux	47	17	37	585
Paris Toulouse	54	20	43	679
Paris Strasbourg	39	14	31	492
Paris Nantes	30	11	24	385
Lyon Marseille	25	9	20	314
Lyon Bordeaux	45	16	36	556
Marseille Toulouse	33	12	26	403
Marseille Montpellier	14	5	11	170
Bordeaux Toulouse	19	7	15	246
Toulouse Montpellier	19	7	15	243
Paris Rennes	28	10	22	354
Major to secondary cities				
Paris Lille	18	6	14	219
Paris Amien	12	4	9	144
Paris Reims	11	4	9	144
Paris Rouen	11	4	9	136
Paris Le-Mans	16	6	13	213
Lyon Grenoble	8	3	6	111
Lyon Clermont-Ferrand	13	5	10	165
Lyon Dijon	16	6	13	196
Lyon Chambéry	8	2	6	108
Marseille Aix-en-Provence	3	1	1	33.2
Marseille Avignon	8	3	6	105
Marseille Toulon	5	1	4	66.3
Bordeaux Poitiers	20	7	16	258
Bordeaux Pau	17	6	13	217
Toulouse Carcassonne	7	2	6	94.1
Montpellier Nîme	4	1	3	56
Strasbourg Metz	13	4	10	165
Nantes Rennes	9	3	7	113
Nantes Angers	7	2	5	91.6
Secondary to secondary cities				
Lille Calais	9	3	7	111
Rennes Saint-Malo	5	2	4	69.5
Rennes Caen	15	5	12	186
Nice Cannes	3	1	2	33.1
Le-Havre Rouen	7	2	5	92.6
Nancy Metz	4	1	3	56.7
Tours Le-Mans	7	2	6	104
Tours Poitiers	8	3	6	112
Dijon Besançon	7	2	6	96

Prices are in euro. The return routes are not listed here. They belong to the same category as their pairs and share the same reference distance.

C.7 Selection of Prediction Models

We select the prediction model by the following steps. Firstly, we rely on the following route-specific variables to form our prediction models, namely, the multiple of the log of the GDP per capita at city level, the multiple of the log of the population at urban area level, the multiple of the unemployment rate at departement level, the distance between two cities, a direct TER indicator, and a direct TGV indicator. Next, we limit the maximum degree of polynomials to two in a regression, meaning that the prediction model may include the square of distance or the interaction of the GDP per capita and the population but not the cubic of GDP per capita or the square of distance times the unemployment rate. We form the regression models based on all possible combinations of the explanatory variables given the constraint on the polynomial degree, compare their BICs, and select the best five models. Finally, we apply 10-fold cross-validation on these five models and choose the one with the best predictive power.

To predict whether a route is in the observed sample, the following model is the best according to minimizing prediction error and is thus chosen to compute the propensity score:

$$\mathrm{Prob}(\mathrm{Observed}_i) = \frac{1}{1+\exp(-f)} \tag{C.1}$$

where $f = \gamma_0 + \gamma_1 \mathrm{GDP}_i^2 + \gamma_2 \mathrm{Pop}_i + \gamma_3 \mathrm{GDP}_i \mathrm{Pop}_i + \gamma_4 \mathrm{Dist}_i + \gamma_5 \mathrm{Unemploy}_i + \gamma_6 \mathrm{TER}_i + \gamma_7 \mathrm{TGV}_i$. The predicted probability is the propensity score (PS_i).

By the same logic, we can directly predict the consumer surplus based on the route-specific characteristics, referred to as Method 1a in the main text. The following model is chosen:

$$\begin{aligned}
\mathrm{CS}_{it} = {} & \mathrm{dow}_t + \mathrm{month}_t + \mathrm{strike}_t + t + \tau_0 \mathrm{TER}_i + \tau_1 \mathrm{TGV}_i + \tau_3 \mathrm{GDP}_i + \tau_4 \mathrm{Pop}_i + \tau_5 \mathrm{Dist_i} \\
& + \tau_6 \mathrm{Unemploy}_i + \tau_7 \mathrm{GDP}_i^2 + \tau_8 \mathrm{GDP}_i \mathrm{Pop}_i + \tau_9 \mathrm{GDP}_i \mathrm{Dist}_i + \tau_{10} \mathrm{GDP}_i \mathrm{Unemploy}_i \\
& + \tau_{11} \mathrm{Pop}_i^2 + \tau_{12} \mathrm{Pop}_i \mathrm{Unemploy}_i + \tau_{13} \mathrm{Dist}_i^2 + \tau_{14} \mathrm{Dist}_i \mathrm{Unemploy}_i + \tau_{15} \mathrm{Unemploy}_i^2 \\
& + \epsilon_{it}
\end{aligned}$$

Aiming to correct the selection bias, we also include the propensity score into the model selection, referred to as Method 1b. The following model is chosen:

$$\begin{aligned}
\mathrm{CS}_{it} = {} & \mathrm{dow}_t + \mathrm{month}_t + \mathrm{strike}_t + t + \theta_0 \mathrm{TER}_i + \theta_1 \mathrm{TGV}_i + \theta_1 \mathrm{GDP}_i + \theta_2 \mathrm{Pop}_i + \theta_3 \mathrm{Dist}_i \\
& + \theta_4 \mathrm{Unemploy}_i + \theta_5 \mathrm{PS}_i + \mathrm{GDP}_i^2 + \theta_6 \mathrm{GDP}_i \mathrm{Pop}_i + \theta_7 \mathrm{GDP}_i \mathrm{Dist}_i \\
& + \theta_8 \mathrm{GDP}_i \mathrm{Unemploy}_i + \theta_9 \mathrm{GDP}_i \mathrm{PS}_i + \theta_{10} \mathrm{Pop}_i^2 + \theta_{11} \mathrm{Pop}_i \mathrm{Dist}_i + \theta_{12} \mathrm{Pop}_i \mathrm{Unemploy}_i \\
& + \theta_{13} \mathrm{Pop}_i \mathrm{PS}_i + \theta_{14} \mathrm{Dist}_i^2 + \theta_{15} \mathrm{Dist}_i \mathrm{Unemploy}_i + \theta_{16} \mathrm{Dist}_i \mathrm{PS}_i + \theta_{17} \mathrm{Unemploy}_i^2 \\
& + \theta_{18} \mathrm{Unemploy}_i \mathrm{PS}_i + \theta_{19} \mathrm{PS}_i^2 + \epsilon_i^{ps}
\end{aligned}$$

C.8 Information about Unobserved (Newly Added) Routes

Table C.3: Unobserved Routes (One Way) and Reference Information

Route	Default	Upper Limit	Lower Limit	Distance (km)
Aix-en-Provence Avignon	5	7	2	85
Aix-en-Provence Draguignan	6	9	3	112
Aix-en-Provence Fréjus	6	9	3	117
Aix-en-Provence Toulon	4	6	2	82
Amiens Arras	3	5	1	101
Amiens Beauvais	3	5	1	61
Amiens Compiègne	4	6	2	99
Amiens Saint-Quentin	4	7	2	82
Angers Cholet	3	5	1	64
Angers Laval	4	6	2	82
Angers Le-Mans	6	8	3	96
Angers Niort	11	15	5	192
Angers Poitiers	8	11	4	212
Avignon Alès	5	7	2	91
Avignon Montélimar	4	6	2	84
Bayonne Pau	6	9	3	112
Besançon Belfort	5	7	2	98
Besançon Bourg-en-Bresse	9	13	4	180
Besançon Chalon-sur-Saône	7	10	3	133
Besançon Montbéliard	4	6	2	83
Bordeaux Agen	8	11	4	140
Bordeaux Angoulême	7	9	3	124
Bordeaux Bayonne	10	15	5	183
Bordeaux Bergerac	6	9	3	119
Bordeaux La-Rochelle	10	14	5	192
Bordeaux Niort	10	15	5	192
Bordeaux Périgueux	7	10	3	137
Brest Quimper	4	6	2	72
Brest Saint-Brieuc	8	11	4	146
Caen Cherbourg-en-Cotentin	7	10	3	123
Caen Évreux	9	13	4	156
Caen Laval	9	13	4	231
Caen Le-Havre	5	7	2	95
Clermont-Ferrand Brive-la-Gaillarde	10	15	5	182
Clermont-Ferrand Le-Puy-en-Velay	7	10	3	128
Clermont-Ferrand Limoges	13	18	6	228
Clermont-Ferrand Montluçon	6	9	3	113
Clermont-Ferrand Roanne	6	9	3	126
Clermont-Ferrand Rodez	13	19	7	245
Clermont-Ferrand Vichy	3	4	1	72
Dijon Auxerre	9	12	4	150
Dijon Chalon-sur-Saône	4	5	2	70
Dijon Épinal	11	15	5	194
Dijon Troyes	10	15	5	185
Douai Saint-Quentin	4	5	2	72
Grenoble Chambéry	3	5	1	57
La-Rochelle Niort	3	5	1	65
Le-Havre Dieppe	6	9	3	114
Le-Mans Blois	8	11	4	146
Le-Mans Chartres	7	10	3	120
Le-Mans Évreux	11	16	5	180
Le-Mans Laval	5	7	2	86

Lille Arras	3	4	1	52
Lille Boulogne-sur-Mer	8	12	4	142
Lille Dunkerque	4	6	2	76
Lille Maubeuge	5	7	2	88
Lille Saint-Omer	4	5	2	69
Lille Saint-Quentin	6	9	3	109
Limoges Angoulême	6	8	3	104
Limoges Brive-la-Gaillarde	5	7	2	94
Limoges Châteauroux	7	10	3	122
Limoges Périgueux	5	8	3	163
Limoges Poitiers	7	10	3	131
Lorient Quimper	4	5	2	70
Lorient Vannes	3	4	1	57
Lyon Annecy	7	11	4	139
Lyon Macon	4	6	2	72
Lyon Roanne	5	8	3	97
Lyon Saint-Étienne	3	5	1	63
Lyon Valence	6	8	3	105
Marseille Draguignan	7	11	4	136
Marseille Fréjus	7	11	4	140
Metz Chalons-en-Champagne	9	13	4	159
Metz Reims	11	15	5	191
Montpellier Albi	11	16	5	235
Montpellier Alès	5	7	2	94
Montpellier Avignon	5	7	2	93
Montpellier Béziers	4	6	2	70
Montpellier Carcassonne	8	12	4	150
Montpellier Narbonne	5	7	2	94
Montpellier Rodez	9	14	5	174
Nancy Belfort	10	14	5	182
Nancy Besançon	11	16	6	204
Nancy Dijon	12	17	6	216
Nancy Épinal	3	5	2	71
Nancy Troyes	14	20	7	244
Nantes Cholet	3	4	1	61
Nantes La-Roche-sur-Yon	3	5	2	70
Nantes Niort	8	11	4	143
Nantes Poitiers	12	17	6	218
Nantes Saint-Nazaire	3	5	1	63
Nantes Vannes	6	9	3	110
Nice Draguignan	5	7	2	89
Nice Fréjus	3	5	1	65
Nice Marseille	11	16	5	198
Nice Toulon	8	12	4	149
Nimes Montélimar	6	8	3	106
Orléans Auxerre	9	13	5	172
Orléans Blois	3	5	1	62
Orléans Bourges	7	10	3	123
Orléans Chartres	4	6	2	80
Orléans Châteauroux	8	11	4	145
Orléans Nevers	9	13	4	198
Paris Auxerre	9	13	4	169
Paris Beauvais	5	8	3	78
Paris Chalons-en-Champagne	10	15	5	188
Paris Chartres	4	7	2	91
Paris Compiègne	4	7	2	79
Paris Évreux	6	8	3	96

Paris Nevers	13	19	7	246
Paris Orléans	7	10	3	133
Paris Saint-Quentin	10	14	5	164
Paris Troyes	10	14	5	178
Perpignan Carcassonne	6	9	3	115
Perpignan Narbonne	4	5	2	68
Poitiers Angoulême	6	9	3	114
Poitiers Cholet	7	10	3	126
Poitiers Niort	4	6	2	75
Reims Charleville-Mézières	5	7	2	87
Reims Compiègne	5	8	2	97
Reims Saint-Quentin	5	8	2	93
Reims Troyes	7	10	3	124
Rennes Angers	7	10	3	127
Rennes Laval	4	6	2	74
Rennes Lorient	8	12	4	151
Rennes Saint-Brieuc	5	8	3	99
Rennes Saint-Nazaire	7	10	3	125
Rennes Vannes	6	9	3	111
Rouen Beauvais	4	6	2	80
Rouen Caen	7	10	3	127
Rouen Dieppe	3	5	1	64
Rouen Évreux	3	5	1	57
Saint-Étienne Clermont-Ferrand	8	11	4	144
Saint-Étienne Le-Puy-en-Velay	4	6	2	75
Saint-Étienne Montélimar	9	13	5	167
Saint-Étienne Roanne	4	7	2	85
Saint-Étienne Valence	7	10	3	122
Saint-Étienne Vichy	8	11	4	142
Saint-Nazaire Vannes	5	7	2	87
Strasbourg Colmar	4	6	2	75
Strasbourg Épinal	8	12	4	211
Strasbourg Mulhouse	6	9	3	117
Strasbourg Nancy	9	12	4	156
Toulon Draguignan	5	7	2	86
Toulon Fréjus	5	7	2	91
Toulouse Agen	6	9	3	115
Toulouse Albi	4	5	2	77
Toulouse Montauban	3	4	1	54
Toulouse Perpignan	11	16	6	206
Toulouse Tarbes	9	12	4	154
Tours Angers	7	10	3	128
Tours Blois	3	5	1	65
Tours Bourges	9	13	4	164
Tours Chartres	10	15	5	202
Tours Châteauroux	8	11	4	186
Tours Cholet	8	12	4	189
Tours Laval	10	15	5	185
Tours Orléans	7	10	3	116
Valenciennes Amiens	7	10	3	126

Prices are in euro. The upper price limit, lower price limit, and default price are retrieved from the BlaBlaCar website in 2019 when the new routes are added. Some routes may have modified regulated prices from 2018 to 2019 (we see some modifications in the observed route sample). However, there should only be 1 € difference. The return routes are not listed here as they share the same reference distance.

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RÉSUMÉ

La société moderne est confrontée à plusieurs défis causés par les voitures. Dans les villes urbaines, trop de voitures sur la route créent des embouteillages, de la pollution de l'air et du bruit. Dans les villages ruraux, les habitants deviennent de plus en plus dépendants de la voiture, ce qui limite le droit à la mobilité de la population vulnérable. Le covoiturage pourrait être une solution aux deux défis. La thèse tente de comprendre le comportement des participants au covoiturage. Les deux premiers articles sont deux expériences de terrain avec Ecov sur les motivations monétaires et prosociales des conducteurs. Pour les voyages de très courtes distances, les motivations prosociales sont plus importantes pour promouvoir la pratique, tandis que pour les voyages de moyenne distance, les incitations monétaires sont plus importantes. Cependant, mettre un incitatif monétaire très élevé ne surpasse pas un incitatif inférieur mais suffisant. Le troisième article examine l'impact de la grève des cheminots français en 2018 sur le covoiturage en utilisant les données de BlaBlaCar. En moyenne, un jour de grève fait augmenter l'offre de sièges en covoiturage de 7% et la demande de sièges de 29%. Le surplus du consommateur, dans toute la France, augmente 17 753 € lors d'une journée de grève moyenne.

MOTS CLÉS

Covoiturage, Motivations Prosociales, Expérience de Terrain, Grève SNCF

ABSTRACT

Modern societies are faced with multiple challenges caused by widespread car usage. In urban cities, too many cars on the road are creating traffic jams, air pollution, and noise. In rural villages, residents are becoming more and more dependent on cars, limiting the mobility rights of a vulnerable population. Ridesharing could be a solution to both challenges. The thesis adds to the understanding of the behavior of ridesharing participants. The first two papers are two field experiments with Ecov on the monetary and prosocial motivations of drivers. For trips of very short distances, prosocial motivations are more salient for promoting the practice, while for middle-distance trips, monetary incentives are more salient. However, putting a very high monetary incentive does not outperform a lower but sufficient one. The third paper examines the impact of the French railway worker strike in 2018 on long-distance ridesharing using data from BlaBlaCar. An average strike day induces the ridesharing seat supply to increase by 7% and the seat demand to increase by 29%. The ridesharing passengers' consumer surplus also increases by 17,753 € during an average strike day across the whole of France.

KEYWORDS

Ridesharing, Prosocial Motivations, Field Experiment, SNCF Strike