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Highlights

- Our paper investigates how prices are determined on peer-to-peer markets
- We analyze whether experience and reputation in sharing economy platforms have the same impact as in traditional markets
- We provide the first empirical analysis of the world’s leading intercity carsharing platform, BlaBlaCar
- We show that more-experienced drivers on BlaBlaCar set lower prices and sell more seats than less-experienced drivers.
- We find evidence of discrimination against drivers of a minority group (Arabic drivers) that sell less seats on Blablacar.

What Drives Pricing Behavior in Peer-to-Peer Markets? Evidence from the Carsharing Platform BlaBlaCar*

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Abstract: We examine how price and demand are determined on peer-to-peer platforms and whether experience and reputation have the same impact as in traditional markets. We use data from the world's leading intercity carsharing platform, BlaBlaCar, which connects drivers with empty seats to riders. We find that pricing decisions evolve as drivers gain experience with the platform. More-experienced drivers set lower prices and, controlling for price, sell more seats. Our interpretation is that more-experienced drivers on BlaBlaCar learn to lower their prices as they gain experience; accordingly, more-experienced drivers earn more revenue per trip. In total, our results suggest that peer-to-peer markets such as BlaBlaCar share some characteristics with other types of peer-to-peer markets such as eBay but remain a unique and rich setting in which there are many new insights to be gained.

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Introduction

The rise of the "sharing economy" (also known as the "collaborative" or "on-demand" economy), and the success of platforms like AirBnB and Uber have attracted the attention of economists and other academics as well as the popular press (Horton and Zeckhauser, 2016). Einav et al. (2016) define these platforms as peer-to-peer markets and emphasize their role in connecting individuals that can be either sellers, buyers, drivers, or workers, and enabling transactions that would not be possible in traditional markets.[1] Peer-to-peer markets are increasingly used for transportation, lending, accommodation, home services, deliveries, or task assignments (Sundararajan, 2016). Peer-to-peer platforms have been argued to provide important efficiency gains (Edelman and Geradin, 2015). Specifically, they lower search and transaction costs (e.g., reduce information asymmetries) and allow fuller use of resources (e.g., increase car occupancy). However, our understanding about pricing behavior and market outcomes on peer-to-peer platforms is still limited.

Our paper investigates how price and demand are determined on peer-to-peer markets and whether experience and reputation have the same impact as in traditional markets. We define experience as a seller with a long tenure in the market and reputation as a seller with a lot of good feedback from past buyers. There is a lot of evidence that buyers are willing to pay more for items sold by sellers with good reputation (Bolton et al. 2013; Cabral and Hortacsu, 2010; Jin and Kato, 2006; Melnick and Alm, 2012; Resnick et al., 2006). Sellers also care about their own reputation. Inexperienced sellers use reputation-building strategies, and they tend to charge higher prices as they accumulate

[1] Similarly, Rochet and Tirole (2006) and Evans et al. (2011) define these platforms as two-sided markets that bring together two groups of economic agents: sellers and buyers, hosts and guests, or drivers and riders.

experience and ratings (Jolivet et al., 2016). These questions have been extensively studied in the context of marketplaces like eBay or AmazonMarketplace (e.g., Cabral, 2012; Dellarocas, 2003; Tadelis, 2016). It is important to investigate whether experience and reputation can have similar effects on platforms where sharing is a key element of the transaction, most sellers are non-professional, and users' feedback concerns the social experience rather than exclusively the product (Zervas et al., 2015; Fradkin et al., 2014).

In this paper, we focus on intercity ridesharing platforms. With intercity carpooling, drivers and riders share the space within the car together for up to a few hours. Because of these face-to-face interactions, there is a much larger scope for driver and rider characteristics to matter and for behavior to evolve in interesting ways as users gain experience on the platform. Our data come from the leading carpooling platform, BlaBlaCar, which is valued at $1.5 billion as of 2015. BlaBlaCar connects a driver with empty seats to riders to share an intercity trip. The importance of BlaBlaCar has been emphasized by Sundararajan (2016), calling it "the company that dominates [the intercity carsharing] market" and noting that BlaBlaCar moves "as of 2015, more people every day than the US national rail system Amtrak" (Sundararajan, 2016 p. 12).

We use this empirical setting to study the determinants of price setting and demand behavior in order to understand how we should expect these types of peer-to-peer markets to evolve moving forward. The BlaBlaCar setting is uniquely well suited for our study because its price-setting environment is different from other carsharing peer-to-peer markets. On platforms like Uber and Lyft, pricing is centralized by the market maker and thus price is the same for any driver offering a given trip at a given moment. In contrast, on BlaBlaCar, pricing is decentralized: drivers set their own price for each trip. Further, all drivers on BlaBlaCar are non-professional. This provides rich price variation and interesting price dynamics as drivers gain experience on the platform.[2]

We collected a large data set on the French carsharing market, which is the home market of BlaBlaCar. Our econometric model addresses the endogeneity of the driver's price and, controlling for price, models demand. Our two sets of main results concern a driver's level of experience and demographic characteristics. First, we focus on how drivers' price-setting behavior evolves as they gain experience on the platform. The results suggest that more-experienced drivers set lower prices and sell more seats than less-experienced drivers. The price result is counter to evidence from other offline and online markets, firms with more experience in the market commonly charge higher prices.

Our finding that drivers lower their prices as they gain experience suggests that learning is important in understanding price setting on sharing platforms like BlaBlaCar. Specifically, we find that drivers learn to set lower prices and earn more revenue per trip over time. The effects we document are not being driven by riders' responses to drivers' reputation. These new insights are important relative to the large literature on peer-to-peer markets such as eBay, where demand-side responses to reputation have been the focus (Cabral, 2012). Our results highlight the important role of supply-side changes in pricing behavior as drivers gain experience on the carpooling platform. We conclude that prices and market outcomes on "sharing platforms" such as BlaBlaCar are determined differently than on marketplaces such as eBay.

[2] BlaBlaCar provides distinct measures for driver's experience and reputation, which allow us to estimate their respective effects. Reputation is about whether the driver can be trusted by riders and is measured by the quantity and quality of feedback left by riders. Experience is about whether the driver has a good understanding of how the carsharing market works, and is measured by a status indicator that takes five values from newcomer to ambassador.

Second, we find the demographic characteristics of a driver have strong predictive power for her price and the demand for her seats. Matching drivers' first/given names to a database of names and their predominant country or region of origin, we classify drivers based on names that are common in our setting of interest, France. Comparing French-sounding names to Arabic-sounding names, drivers with a predominantly French name sell more seats and drivers with a predominantly Arabic name sell fewer seats. An Arabic name is associated with a particularly strong negative effect on demand and reduces driver revenue substantially. Our findings are related to the growing empirical literature on digital discrimination, including studies of AirBnB (Cui et al. 2016, Edelman and Luca, 2014, Edelman, Luca, and Svirsky, 2018, and Kakar et al. 2017), Craigslist (Doléac and Stein, 2013), Uber (Ge et al., 2016), and Prosper.com (Pope and Sydnor, 2011). These studies show evidence of discrimination on both sides of the market (toward suppliers and demanders) and seek to understand the underlying mechanisms (statistical versus taste-based discrimination).

The paper is organized as follows. The next section introduces BlaBlaCar. Section 2 describes our data and Section 3 explains the empirical methodology to analyze market outcomes and address the simultaneity of price setting and demand. Section 4 presents the main econometric results and Section 5 presents revenue results. Section 6 explores the mechanisms that drive our results, while Section 7 concludes.

1. The carsharing platform BlaBlaCar

Founded in France in 2006, BlaBlaCar has become the leading carsharing platform.[3] BlaBlaCar offers intercity ridesharing services, connecting drivers with empty seats to people who are traveling on the same trip (see Figure 1). Drivers earn money and passengers save on travel expenses (given that the typical trip on BlaBlaCar is cheaper than the corresponding train ticket). As of 2017, BlaBlaCar operates in 22 countries (mainly in Europe, but also in Mexico, India, Russia, and Brazil) and has more than 40 million members. In April 2015, BlaBlaCar acquired the second largest European carsharing company Carpooling.com. BlaBlaCar has not seen the types of regulatory battles faced by carsharing companies like Uber, because BlaBlaCar is considered a not-for-profit ride service. The stated purpose of the money received by drivers is only to share the cost of the trip.

Over 3 million people use BlaBlaCar every month, around 29% of whom are drivers. The average BlaBlaCar user is 34 years old, with 14% of drivers and 36% of passengers being students. Registration on BlaBlaCar is free but passengers pay fees that are about 15% of the price of the ride paid to the drivers.[4] Like most other peer-to-peer markets, passengers and drivers are asked to rate each other and write reviews.

For each trip, BlaBlaCar suggests a "recommended price" based on the trip distance and the estimated price of fuel and tolls.[5] The recommended price does not depend on the

[3] The name BlaBlaCar comes from the French word "blabla" that is the English equivalent of blah. Drivers can display their "talking" preference in their profile: Bla if they do not like to talk with passengers, BlaBla if they like to talk a little, and BlaBlaBla if they like to talk a lot.
[4] As of 2015, booking fees and value added tax (VAT) are added to the price that the passenger pays to the driver. The fees earned by BlaBlaCar are composed of a fixed component (€ 0.89) and a variable component (9.90%, of the price). A VAT of 20% is added to these fees.
[5] For instance, in 2015, the recommended price of BlaBlaCar was automatically calculated as follows: .065 € per kilometer and per seat if the driver takes a toll road and .048 € per kilometer and per seat otherwise.

number of seats offered by the driver or the comfort of the car. Then the driver can adjust the price up or down, with the minimum (maximum) price set as 50% (150%) of the recommended price. In February 2012, BlaBlaCar introduced a price color classification, where the driver's price appears to potential riders as green if the driver chooses a price that does not exceed the recommended price. Otherwise, the price is orange (up to 125% of the recommended price) or red (between 125% and 150%).

2. Data collection

Data were collected daily from August 2013 to March 2014. BlaBlaCar displays a listing of the most popular French intercity trips on its website, which covered all regions of France including all provincial cities with more than 100,000 inhabitants. From this list, we sampled 40 intercity trips with the highest number of offers in early 2013, which ensures a sufficiently large sample. Among these 40 trips across France, we have trips between provincial cities as well as trip between Paris and a provincial city. The list of trips is available in the appendix, including descriptive statistics (distance, number of observations, and unique drivers for each trip). There are 41 unique cities (33 of more than 100,000 inhabitants and 8 of less than 100,000 inhabitants). The shortest trip is Nimes-Montpellier (56 km) and the longest trip is Paris-Marseille (774 km).

The data collection procedure was automated. For each trip, we collected all offers, resulting in 920,789 observations (i.e., an observation is a trip between two cities, with a departure date and hour, posted by a driver). The data collection script scraped the BlaBlaCar website, resulting in multiple snapshots of each observation (e.g., three days before departure, two days, departure day). We focus on the last observation for each trip.

The data contain the departure and arrival cities; departure date and hour; driver name; profile (gender, age, etc.); whether the driver's photo is shown; and declared preferences for smoking, pets, and music.[6] For each trip, we have the number of seats available, the price, and price color (green, orange, or red). If all seats are sold before the departure, the trip continues to show in the search results with the label "Full." This is the case in 54% of the trips in our data set.

Our empirical analysis requires that we precisely identify drivers. Unfortunately, unlike other online marketplaces, BlaBlaCar does not use unique user IDs as part of its listing interface, an approach that is useful with eBay data, for example. As a result, we need to identify drivers as carefully as possible to identify which listings were offered by the same driver. To do so, we use three variables in our data: name, age, and gender. It is important to note that we have name information on the driver's first/given name as well as the first initial of the driver's last name. Coupled with age and gender, we are able to classify drivers with a high degree of precision.[7] For these 294,419 individual drivers, they are 36 years old, on average, and around 40% of listings are by females.

We also collected the ratings and the status of drivers that are publicly observable by riders. When these data were collected, the rating mechanism of BlaBlaCar allowed only a positive or negative rating. In our data set, members' reputation is, therefore,

[6] We also attempted to collect data on drivers' preferences for talking (dislikes talking, likes a little talking, or likes a lot of talking). The data for this variable indicate that all drivers set this preference to "a lot," which suggests that our scraping software did not correctly extract this variable. As a result, we cannot control for drivers' talking preference.

[7] To verify our procedure for identifying drivers, we consider data on the comfort rating of the driver's car, whether she allows smoking, whether she allows pets, and whether she requires manual confirmation. When we additionally add these four variables as inputs into our driver identification procedure, only 18 drivers are identified differently between the two approaches. This represents 0.01% (i.e., one-tenth of one percent) of our drivers. This suggests that we are identifying drivers precisely.

measured by the number and percentage of positive ratings that were received.[8] The status of the driver is also a key driver characteristic. A driver is classified as newcomer, intermediate, experienced, expert, or ambassador, based on four criteria (% of profile completion, number of ratings, % of positive rating, and seniority). To be an ambassador, the driver needs to complete 90% of her profile (name, gender, preferences, short bio, car comfort, and photo), to receive at least 12 ratings (with more than 90% of positive ratings) and to have a tenure of at least 12 months.[9] Table 1 shows the criteria of classification for status. Controlling for reputation, a driver's five-level status measures her experience level.

[Insert Table 1]

We also collected the comfort of the driver's car on a 4-level scale, where higher values indicate a more luxurious vehicle. Comfort is self-classified by the driver (basic, normal, comfortable, or luxury) and 11.36% of drivers do not disclose any comfort level. However, we have no information on the make or model of the car (or fuel efficiency).

Table 2 presents summary statistics. Panel A presents our explanatory variables, including each driver only once, while Panel B summarizes the outcomes of interest for the entire sample at the trip level (price and quantity). The variables in Table 2 are those described earlier in this section.

[Insert Table 2]

Regarding drivers (panel A), the number of ratings received is 8.4 on average, while driver status is 2.7 and car class is 2.3 on average. Using a database of names and associated country/region of origin, we classify drivers by the most prominent region of

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[8] As of 2015, BlaBlaCar's rating system has expanded to include a five point scale.
[9] Most of profile information is required at the registration, but some remains optional like displaying a photo or linking her profile to her Facebook account.

origin of their first/given name.[10] Our approach classifies 67% of drivers as having a French-sounding name (e.g., Guillaume, Pierre, and Sophie), 5% as having an Arabic- or Muslim-sounding name (e.g., Ahmed, Mariama, and Youssef), and the remaining 28% as having a name that is neither predominantly French nor Arabic (e.g., Kim, Mickael, and Tony).

Further, drivers include a picture with their profile in 39% of cases. 56% of drivers indicate that they play music during the trip, 9% allow pets, and 7% allow smoking. Finally, 26% of drivers offer roundtrip travel, while 12% of drivers allow a seat to be sold only after manually confirming the sale. The alternative to manual confirmation is that the passenger's trip is confirmed instantly, which is similar to Instant Book on AirBnB.

Regarding trips (panel B), the price per seat is measured in integer euros. In our data set, the average price for a trip is around 13 euros, with substantial variation (standard deviation of 9.4 euros). Next, relative price is shown, which is the driver's price minus BlaBlaCar's recommended price. The average price is 2.8 euros *lower* than the recommended price. This implies that the recommended price is not serving as a de facto market price. To provide further evidence on this point, Appendix Table A2 tabulates drivers' relative prices. The recommended price is not the modal price; the most common prices are one and two euros lower than the recommended price. These results suggest that pricing on BlaBlaCar is decentralized, as we have argued. When we group drivers according to their status level, ranging from one to five for newcomer, intermediate,

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[10] We collected data on names origin from three web sources: www.insee.fr (the French National Institute of Statistics and Economic Studies) and two well-known French websites: http://www.prenoms.com and http://www.signification-prenom.net. The resulting database contained over 69,000 first/given names along with their country of origin, which was cross-checked across these three websites for accuracy.

experienced, expert, or ambassador, we find that prices fall as drivers gain higher status levels.

Table 2 also displays the two quantity measures that we use in our regressions: the *fraction of listed seats that sold* and the *all seats sold* dummy variable. To obtain the first measure, we rely on the panel nature of our data with repeated listings for a given driver. The data-extraction software used to gather data regularly visited hundreds of thousands of BlaBlaCar listing pages but instantaneous data collection is infeasible. As a result, the data occasionally contain a number of seats available that already reflects a lower quantity than the true quantity supplied. That is, when the software scraped a given listing's page, the number of seats available may already be lower by one seat if a rider purchased a seat before the page was first scraped. While the data collection may miss a seat sold for a driver on a given listing, it is unlikely to systematically miss seats sold on all listings that a driver ever offers. As such, we construct a variable that is equal to the maximum number of seats offered ever observed by the driver across all of her listings (seats in car).[11] Then the fraction of seats sold is equal to the number of seats sold divided by the maximum number of seats offered by the driver (as defined above). The proportion of seats that sold for a listing varies between zero (all seats are unsold) and one (all seats are sold); the average is 0.62.

The second measure is more straightforward: *all seats sold* is a dummy variable that equals one when the number of seats available equals zero at the close of the listing. Importantly, the all seats sold dummy is robust to our approach for measuring the number of seats available in the car. While we imperfectly observe the number of seats initially offered, we perfectly observe the number of seats still available for each listing,

[11] We do not have data on the make and model of the car and instead have only a measure of the comfort level of the car.

irrespective of how soon or how often the data-extraction software gathered data on a listing. If zero seats are available when the listing closes, then all seats sold, by definition. The two quantity sold measures provide similar results in what follows, providing support for our approach for defining quantity sold.[12]

3. Econometric Model

To understand the functioning of the BlaBlaCar carsharing platform, we perform a regression analysis to explain the prices charged and quantities sold by drivers. We also consider revenue but defer discussion of our revenue analysis until Section 5. We use data listed on BlaBlaCar starting from August 2013 until March 2014. The resulting data set contains 920,789 listings from 294,419 distinct drivers.

The outcomes of interest are price and quantity sold. We present an instrumental variables regression analysis, where price is considered an endogenous variable that affects quantity sold. Our econometric model is a two-stage least-squares fixed-effects panel-data regression on both price and quantity, with trip fixed effects. A trip is defined as a departure city-arrival city pair. Including trip fixed effects allows us to control for the general characteristics of the trip, then look separately at specific factors that affect drivers' prices and riders' demand.

For price, the model is a linear regression. By using trip fixed effects, our price measure is analyzed in a comparable way across trips (i.e., trip fixed effects control for the

[12] We could alternatively use the number of seats sold in our demand regressions. However, doing so is problematic because it treats different sized cars (small cars versus large sports utility vehicles) differently, which could create endogeneity issues if different types of drivers have different sized cars in ways that are unobservable and related to our explanatory variables of interest (e.g., age or gender).

average price across all listings of the trip). For the fraction of seats sold and the all seats sold dummy variable, we again use linear regression. Our use of linear models is consistent with the approach advocated by Angrist and Pischke (2008). In all specifications, continuous explanatory variables are included in quadratic form, with the results shown as the average marginal effects. Allowing the explanatory variables to have nonlinear effects is more flexible and several variables should be expected to have a nonlinear effect (e.g., price on demand).

To control for price endogeneity, we construct instruments from the trip-level panel nature of our data. Specifically, we link drivers who offer a given trip to other trips offered by the same driver to infer the average characteristics of "trips other than the trip in question." For example, suppose a driver is only ever observed offering trips from Lyon to Grenoble and from Lyon to Paris. If Lyon to Grenoble is the trip in question, then Lyon to Paris trips refer to the "trips other than the trip in question." We instrument for the price of a seat by using the average price charged by the same driver on "all trips other than the trip in question". For the drivers who only ever offer one trip, there are no such trips. We refer to these drivers as single-trip drivers and, for these drivers, the average-other-price instrument equals zero. This instrument is essentially a combination of two distinct characteristics of drivers. First, does the driver offer trips between a pair of cities that is different from the pair of cities in question? This factor determines whether the instrument is positive. Second, if yes, did the driver set prices that were high or low, on average, on those other trips? This factor determines the continuous variation in the instrument. Our instrument essentially combines a dummy variable for whether the driver offers trips other than the trip in question and, if so, a continuous variable measuring average price on those trips.

The intuition behind the “average-other-price instrument” is that a combination of observed and unobserved characteristics of the driver affects the price she sets. Because the econometrician has access to all observed characteristics, the variation in price that is affected by the unobserved characteristics should be highly correlated across the driver’s listings on the trip in question and her listings on trips other than the trip in question.[13]

Further, we believe that the average-other-price instrument is plausibly exogenous because it reflects underlying factors about the driver that should not affect demand except through the price set on the listing in question. It is useful that we have a large number of alternative trips because constructing the average price the driver set for other listings on the same trip is likely to itself be endogenous; such an average-same-price instrument is problematic because potential riders might observe a given driver offering a given trip across multiple listings of the trip (with different departure dates). By using the average price on trips other than the trip in question, we greatly reduce the possibility that riders have any sense of where the driver falls in the price distribution for other trips. In Table 2, the average-other-price variable averages around 11 euros, while just over half of the drivers in our sample only ever offer one trip. The average-other-price instrument equals zero for these drivers, which represent 21.1% of the total number of observations.

[13] In Appendix B, we discuss a set of robustness checks using two sets of alternative instruments. The first set of alternative instruments use the one week lag of characteristics of other drivers on the same trip in the prior week. These instruments are exogenous under the argument that past trips reflect underlying supply characteristics that affect contemporaneous price in exogenous ways conditional on observables. The second set of alternative instruments use characteristics of other drivers on the driver's modal trip (other than the trip in question) during the same week. These instruments are exogenous under the argument that drivers’ pricing behavior is affected by their competitive interactions in the other markets where they drive. The results are robust across these very different IVs.

Our instrument is in the spirit of commonly used instruments in the Industrial Organization literature, which are often called BLP instruments, following Berry, Levinsohn, and Pakes (1995). This cross-market feature of our instrument is shared with the empirical Industrial Organization papers using these type of BLP instruments.

4. Empirical Results

Using the average-other-price instrument, we conduct an instrumental variables panel regression analysis with trip-fixed effects, where the first stage asks what factors affect the driver's price and the second stage asks what factors affect the quantity sold, controlling for the endogeneity of the price in its determination of quantity sold. As explained earlier, price is measured in integer euros and quantity sold is measured in two ways: the fraction of seats sold and a dummy variable that equals one if all seats sold.

Table 3 presents the determinants of the drivers' price with and without the average-other-price instrument. Column (2) with the instrument serves as the first-stage of our IV regression analysis. The use of trip fixed effects implies that the variation we exploit is the driver's price relative to the average price on the trip. This controls for time-invariant trip characteristics such as distance. We also control for departure time of day, day of week, and a time trend (see appendix Table A3).[14]

[14] We include an analysis with driver fixed effects in Table 6 and confirm the main results. We prefer trip fixed effects for two reasons: (1) within-driver results exploit different variation than our main analysis that exploits between-driver variation and (2) within-driver analyses require us to restrict the sample to drivers with enough trips and might limit our ability to learn something about very new drivers or drivers who offered a few trips and exited the platform.

First, we discuss the validity of our instrument, then we discuss the results for price along with the results for demand. In Column (2), the average-other-price instrument (average price on trips other than the trip in question) is highly statistically significant. Increasing the price on other trips by one euro is associated with a one cent higher price. The size of this effect suggests that the latent characteristics of the driver that introduce a correlation between prices on different trips are statistically meaningful but quantitatively small. This implies that trip-specific factors (e.g., the recommended price) are more important than driver-specific factors in pricing but driver-specific factors are sufficiently important to ensure the strength of the average-other-price instrument.

[Insert Table 3]

The first-stage F statistic that is shown in Table 3 equals 1939.0, which is very large and considerably above the rule-of-thumb of 10 in order to mitigate concerns about weak instruments (Angrist and Pischke 2008). Further, we measure the strength of both components of the variation in the average-other-price instrument: first, the zero/non-zero variation in the instrument of whether the driver offers trips other than the trip in question and, second, the continuous variation in the instrument of the average price on those trips.

To measure the strength in the zero/non-zero variation, we rerun the first-stage weak instrument test with an instrument that equals one if the driver only ever offered a single trip. The first-stage F statistic in this case equals 219.3. We also rerun the first-stage weak instrument test for only multiple-trip drivers to ask whether the continuous variation in the instrument is strongly associated with price. The statistic in this case equals 1886.6. Thus, most of the strength of the instrument comes from the continuous variation but both sources of variation are sufficiently strong to support the use of the average-other-price instrument as a strong predictor of prices.[15] In Appendix B, we discuss a set of robustness checks using two sets of alternative instruments: the average fraction of orange or red prices (above the recommended price) for the prices set by other drivers on the same trip in the prior week, and the average characteristics of other drivers on the driver's modal trip (other than the trip in question) during the same week. The results are very robust, as can be seen by comparing Table 4 to Tables B1 and B2.

To discuss the results, we discuss the determinants of price from Table 3 and of quantity sold from Table 4 together. In Table 4, Columns (1) and (3) present OLS demand regressions for the fraction of seats sold and for the all seats sold dummy respectively, while Columns (2) and (4) present IV demand regressions using the average-other-price instrument to isolate the exogenous variation in the driver's price.

The results for these two measures of demand are very similar, leading us to only discuss Columns (1) and (2). Having a higher price is associated with fewer seats sold, but the effect is much larger when we instrument for price.[16] Controlling for price endogeneity, fraction sold decreases by around 8 percentage points for each one euro higher price, relative to a mean fraction sold of 62%.

[Insert Table 4]

[15] In Table A5, we rerun the demand regressions with only multiple-trip drivers. Comparing the main results in Table 4 to this robustness check in Table A5, we see that the results are extremely similar.

[16] The increase in the (absolute value of the) price elasticity in the IV results is consistent with heterogeneity in pricing behavior that is correlated with the error term in the demand regression, generating attenuation bias in the OLS result.

We have two sets of main results from Tables 3 and 4: driver experience/reputation and driver demographics. We discuss these main results, then the remaining findings.[17]

Driver Experience/Reputation

The richness of our BlaBlaCar data allows us to control for driver reputation, which has been the focus on other studies of online markets, separately from driver experience. Reputation is measured in terms of quantity (number of feedback ratings received) and quality (percentage of positive ratings relative to all ratings received). Holding reputation constant, driver status measures a driver's experience level on the BlaBlaCar platform. On its website, BlaBlaCar defines this five-tier status as the level of driver's experience.[18]

The results suggest that more-experienced drivers set lower prices: drivers with the highest status (ambassador) set prices that are 44 cents lower than drivers with the lowest status (newcomer). This is a moderate effect size relative to a mean price of 13.4 euros; however, this effect represents one of the larger effects of any explanatory variable in Table 3. In contrast, driver reputation has a weak relationship with price. More feedback of a driver has an effect that is essentially zero: moving from 0 ratings to 13.1 (the mean) is predicted to decrease price by 0.5 cents (half a cent). The quality of a driver's reputation (better feedback) has a positive effect that is also small: if a driver's reputation increases from 90% to 100% positive, price is predicted to increase by 5.2 cents.

[17] Note that the Wu-Hausman test of endogeneity of price in the demand estimation provides an *F* statistic of 1543.2 (p-value = 0.00), which rejects the null that price is exogenous and supports our use of an instrumental variables analysis.

[18] We do not directly observe drivers' registration date on the platform or other precise measures of the activity of drivers on BlaBlaCar. However, the labels associated with driver status unambiguously refers drivers' experience on the carsharing platform (newcomer, intermediate, experienced, expert, ambassador) and the highest levels can be reached only if a driver is regularly posting offers.

Turning to Table 4, drivers with more experience sell more seats, controlling for price: ambassadors (highest status level) have a fraction sold that is 5.2 percentage points higher than newcomers (lowest status level). For drivers in the middle status levels (intermediate, experienced, and expert), the effect is around one percentage point but there is a discrete jump in demand for drivers at the highest experience level. Concerning drivers' reputation, more and better feedback is associated with higher quantity demanded: moving from 0 ratings to 13.1 (the mean) is predicted to increase the fraction of seats sold by 0.2 percentage points, while moving from 90% positive to 100% positive is predicted to increase the fraction of seats sold by 2.0 percentage points. As for price, feedback effects remain very small nonetheless.

Overall, we conclude that more-experienced (higher status) drivers set lower prices than less-experienced drivers, with a moderate effect size. Further, more-experienced drivers sell more seats, with a particularly strong effect associated with moving to the highest experience level (ambassador).[19] Drivers with better reputations (in terms of quantity and quality of ratings) sell also more seats and set higher prices. However, these effects are much smaller than the effect of driver experience.[20] Intuition from offline markets suggest that more-established firms typically charge higher prices. Evidence from eBay and other marketplaces shows that seller with more experience are able to sell for higher prices (Cabral and Hortacsu, 2010; Jolivet et al., 2016; Resnick and Zeckhauser, 2002; Resnick et al. 2006). In contrast, we interpret our finding as

[19] Table A4 presents a step-by-step set of regressions that look at the relationship between a driver's level of experience and her price, sequentially adding additional regressors. The main result that more-experienced drivers set lower prices holds in all specifications.

[20] In unreported results, we rerun the price analysis for the most-experienced drivers and for all other drivers separately. The results suggest that more reputation quantity is associated with a 26.9 cent price decrease when moving to the mean of 13.1 ratings for the less-experienced drivers (lower than ambassador status) but there is no additional effect of reputation quantity once a driver reaches ambassador status.

suggestive that new drivers on BlaBlaCar are using a different decision-making process when setting prices than that of experienced drivers. Section 5 provides a discussion of potential mechanisms for the role of experience on pricing behavior, where we separately test for learning and selection effects.

Finally, we present a robustness check of the experience result separately for each trip, using a nonparametric trend test of whether prices fall as driver experience increases. Across all 40 trips, we find that there is a statistically significant decrease in prices as driver experience increases for 37 of 40 trips (exceptions with a statistically significant increase: Lens-Paris, Nice-Toulon, and Rouen-Paris). We notice nothing systematic about these three exceptions (e.g., Lens-Paris has a positive price-experience relationship while Lille-Paris has a negative price-experience relationship, but the two trips are similar in most regards).[21]

Driver Demographics

Our next set of main results concern demographic characteristics of the driver: name origin, gender, and age. As discussed earlier, a driver's first/given name may signal her origin or ethnicity and we match names to predominant country of origin to classify drivers as having a French-sounding name (67% of drivers), an Arabic-sounding name (5%), or a name that is neither predominantly French nor Arabic (28%).

Drivers with a French name set prices that are 3 euro cents higher than the omitted group of all other names. In contrast, drivers with an Arabic name set prices that are around 21 cents lower. Controlling for price, drivers with a French name sell more seats, while drivers with an Arabic name sell fewer seats (fraction of seats sold increases by six percentage points and decreases by seven percentage points, respectively). The

[21] The distance between Lille and Lens is only 36 kilometers.

effect size of having an Arabic-sounding name on BlaBlaCar is similar to that found in work on AirBnB for black, Asian, and Hispanic hosts (Edelman and Luca 2014, Kakar et al., 2017) or on Craigslist for black sellers (Doléac and Stein, 2013). Our results suggest either discrimination or unobserved heterogeneity that is correlated with demographics. However, given our rich set of controls, we believe that there is limited scope for unobserved heterogeneity in explaining why we observe such differences because we control for essentially all of the characteristics that are observed by potential riders. Nevertheless, we use the term discrimination cautiously without conclusive evidence.

Next, we ask whether the driver name effect continues to matter when considering only the most experienced drivers (ambassador status). We find that the negative effect of having an Arabic-sounding name on seats sold is smaller among the most experienced drivers (6.9 percentage points less demand for Arabic names than French names) relative to result among all drivers (13.6 percentage points less demand for Arabic names than French names).[22]

As with the experience result, we measure the effect of an Arabic name separately for each trip, using a t-test of whether Arabic drivers have lower average sales probability than other drivers. Across all 40 trips, we find that there is a statistically significantly lower average sale probability for Arabic drivers for 35 of 40 trips (exception with a statistically significantly higher probability: Amiens-Beauvais, exceptions with no statistically significant difference: Besancon-Dijon, Dijon-Besancon, Metz-Nancy, and

[22] The effect of having an Arabic-sounding name is expressed relative to having a French-sounding name, so the effects reported are the sum of the coefficients for French and Arabic. The full set of results from the robustness checks discussed in this section are available from the authors upon request.

Saint Etienne-Clermont). The presumption of digital discrimination for drivers with a predominantly Arabic name is therefore quite robust.[23]

Regarding gender effects, female drivers set prices that are 12 cents higher than male drivers, on average. Controlling for price, the fraction of seats sold is three percentage points higher for female drivers than for males. The higher demand for rides listed by female drivers may suggest that both female and male riders prefer a female driver, but we do not have data on rider characteristics to test this hypothesis.

Finally, older drivers set higher prices and, controlling for price, sell no fewer seats, on average. Recall that age (along with the other continuous explanatory variables) is included in quadratic form, where the results shown in Table 3 are the average marginal effects. We look for nonlinearities in the effect of age in the Appendix (Figures A1 and A2). There is not much curvature for the effect of an additional year of age on price, but there is a nonlinear effect of age on quantity demanded: among younger drivers, an additional year of age is associated with more sales, while, among older drivers (late 30s or older), an additional year of age is associated with fewer sales.

Other Results

Beyond these main results, several other interesting patterns emerge. Class measures the car's comfort level, where zero represents no indication of the class, relative to values between one (basic comfort) to four (luxurious). The results suggest that, for drivers who do not disclose a class, prices are set as if the car is of average comfort (similar to a class of three). However, controlling for price, undisclosed quality cars are

[23] We also compare Arabic and French names among only those drivers whose car is of the highest comfort level to see if the results can be explained by rider perceiving that a driver with a non-French name might drive a less luxurious car. Among these drivers, Arabic drivers also sell fewer seats than non-Arabic drivers and the effect size is similar to the main results.

associated with fewer seats sold, where these cars sell one percentage point fewer seats than cars of the lowest disclosed comfort level. The demand result is consistent with the unraveling result economists often predict under voluntary quality disclosure. We note that there is a large effect of manual confirmation on price and demand, suggesting a strong preference of riders not to be required to request confirmation of the ride. In Appendix C, we analyze this choice more fully and find that the use of manual confirmation reflects a lack of experience with the platform.

5. Empirical Analysis of Revenue

We have thus far focused on the determinants of price and demand; now we present results on revenue. Revenue is equal to the number of seats sold times the price. The disadvantage of an analysis of revenue is that it does not allow us to disentangle the determinants of supply (which we approach with our price analysis in Table 3) from the determinants of demand (Table 4). However, revenue is the cleanest way to measure the magnitude of the effects that we have documented. We seek to measure the size of the effects of driver demographics and the cumulative effect of driver experience (given that more-experienced drivers set lower prices but sell more seats). Our regression model for revenue is a Tobit model. Table 5 presents these results.

First note in Table 5 that we added the maximum number of seats in the driver's car as a covariate, which did not appear in our earlier analyses. The disadvantage of including seats in car is that the size of a driver's car might interact with other driver characteristics of interest in complex ways. As a result, we did not include seats in car in the price or demand regressions. However, seats in car are a strong determinant of revenue because more seats in the car necessarily imply more seats can be sold. Logically, we find this holds in the results, where one additional seat in the car is associated with seven euros more in revenue.

More importantly, we find that more-experienced drivers earn more revenue per trip, with a meaningful effect of moving to the highest status level. Drivers of intermediate status levels earn around 80 euro cents more than those with the least experience, while drivers with the most experience (ambassador) earn nearly two euros more in revenue. Further, drivers with an Arabic-sounding name earn 1.1 euros less than the omitted group (drivers with neither French nor Arabic-sounding names), while drivers with a French-sounding name earn 7.4 euros more than the omitted group. Comparing French and Arabic-sounding names, Arabic drivers earn 8.6 euros less in revenue. This is an extremely large effect relative to a mean revenue of 14.8 (58.4% reduction in revenue), which gives an estimate of the cost of being discriminated against on a carsharing platform.

Given our emphasis on the price and demand results over the revenue results, we do not present an extended discussion of the remaining results in Table 5. Not surprisingly, most of these other results agree with those from Tables 3 and 4.[24]

[Insert Table 5]

[24] There is one odd result for revenue relative to the earlier tables: females earn around 50 euro cents in revenue less than males. The explanation is that female drivers drive smaller cars than male drivers (seats in car for females is 0.4 seats lower). We rerun the revenue analysis of Table 5 where we interact seats in car with gender and find that a female driver with a given number of seats in her car earns more revenue than a male driver with the same number of seats. For example, a female with three seats in her car earns one euro more in revenue than a male driver with three seats (16.79 versus 15.76).

6. Testing Explanations Based on Learning versus Selection

Two separate mechanisms could account for the negative relationship we document between a driver's experience and her price. A first explanation involves learning: drivers learn to lower their prices as they gain experience. A second explanation involves a selection effect: drivers who offer low prices on sharing platforms are more likely to gain a lot of experience. To provide evidence on the relative importance of these two explanations, we first use within-driver price dynamics to test for a learning effect, while accounting for selection. Then, we test for the degree to which selection exists.

Table 6 explores the determinants of price-setting behavior additionally including driver fixed effects, which controls for the difference in price levels across drivers and exploits variation in price changes for a given driver over time. The question of interest is whether a driver sets lower prices when she has more experience relative to the prices she set when she had less experience.

[Insert Table 6]

Table 6 presents the results for all drivers with at least eleven listings, which includes 12,989 individual drivers and 276,178 observations.[25] In the econometric specification, the included covariates are driver feedback quantity and quality, driver experience, departure characteristics, trip fixed effects, and driver fixed effects (i.e., all time-varying covariates plus fixed effects).

Table 6 confirms that drivers lower their prices as they gain experience, thus supporting a learning explanation for our earlier results. Specifically, controlling for changes in a

[25] Eleven listings is chosen based on the next set of analyses, which splits a driver's tenure into early (first ten listings) and late (listings eleven and later).

driver's feedback, moving to a higher level of experience is associated with lower prices. Our interpretation is that drivers are induced to set lower prices as they gain experience, because they learn about profit maximization over time (e.g., learn that lower prices increase demand enough to raise profits) and about utility maximization over time (e.g., learn that they enjoy the platform and the socialization it provides). To conclude our analysis of a learning explanation versus selection, we test the degree to which drivers with a lot of experience appear to be a selected sample.

To do so, we split each driver's tenure on BlaBlaCar during our sample period into two periods, a driver's first ten listings versus all later listings. Then, we summarize the driver's early-tenure prices to categorize drivers into four quartiles based on their prices during the first ten listings. To deal with price differences across trips and other factors that affect prices, we use relative prices (i.e., the driver's price minus the recommended price) to calculate the driver's average relative price during the early part of her tenure. Drivers are classified into four early-tenure price categories based on the four quartiles of the average relative prices. We only include drivers who we initially observe as a newcomer (status of one); this ensures that the pricing behavior we characterize as early in a driver's tenure is in fact when she was (literally) a newcomer to the platform. We further only include drivers with at least eleven listings so that we can observe the first ten listings.

The results in Table 7 suggest that there is not a monotonic pattern in a driver's number of late-tenure listings as a function of her early-tenure prices: the highest-priced drivers (category four) have 11.34 late-tenure listings, on average, while the lowest-priced drivers (category one) have 10.99 late-tenure listings. Further, drivers whose relative prices were in the third quartile of the price distribution have the most late-tenure listings (11.79). This nonmonotonic pattern is inconsistent with the selection explanation (which says that the most-experienced drivers are a selected sample of drivers who have consistently set low prices since their first listing on the platform). These results suggest that selection is not driving our results. Along with the results in Table 6, we conclude that drivers learn to lower prices as they gain more experience on the platform.

[Insert Table 7]

This evidence suggests that learning, not selection, drives our main result that BlaBlaCar drivers with more experience set lower prices. Our final exercise is to document the types of pricing strategies that drivers use over time and how they learn from their initial BlaBlaCar experiences. This illustrates which types of drivers are lowering their prices and to what extent. The results are shown in Table 8. We again categorize drivers based on the first ten listings, here based on the fraction of seats sold on average during the early-tenure trips. We are interested in which drivers lower their prices more or less as a function of how many seats they sold on average early in their tenure. The prices shown in Table 8 are the predicted relative price[26] charged by drivers across their tenure on the platform, using the regression model from Table 3. Column (3) shows the initial price, which is the average relative price measured for drivers' first observed trip; Column (4) shows the later price, which is the average relative price measured for drivers' who have had the average number of trips (17.2). Finally, Column (5) shows the price change from initial price to later price along with the standard error of the difference.

[26] Using predicted relative price allows us to control for other observed factors that affect price and look at ceteris paribus effects of early trips on late trips.

[Insert Table 8]

Table 8 shows that the "learning to lower prices" result is driven by drivers who sold none of their seats early in their tenure on the platform. The effect is monotonic in first-half sales rate: 44 cent reduction for drivers who sold no seats initially, 12 cent reduction for those who sold less than half but some seats, and 4 cent reduction for those who sold more than half but not all seats. For the drivers who sold all seats in all early listings, the learning effect is a price increase of 45 cents. These results intuitively reflect that the pricing dynamics we observe are explained by drivers who appear to have been pricing too high early in their tenure. The result is also consistent with driver who initially experienced no socialization benefits from the platform (drove in an otherwise empty car) learning to price in ways to attract riders.

7. Discussion and Conclusion

Despite the increasing importance of carsharing, these platforms have received only limited econometric analysis. Our paper studies the largest intercity carsharing platform in the world to understand the functioning of these type of peer-to-peer markets. We are particularly interested in assessing how much of our understanding from the literature on other types of peer-to-peer markets such as eBay carries over to the "new sharing economy" such as BlaBlaCar. The peer-to-peer markets in the latter category allow both online and offline interactions between users. As a result, price-setting and demand behavior are likely to present novel insights relative to the large literature that studies these questions using data from marketplaces such as eBay.

The main advantage of using BlaBlaCar to study pricing and market outcomes is that prices are set by individual drivers, relative to a "recommended price" that is suggested by BlaBlaCar. In contrast, on other peer-to-peer markets in the transportation sector such as Uber and Lyft, price setting is centralized and thus any driver offering a given trip at a given moment has the same price. Our focus is on experience in pricing setting, thus decentralized pricing is important to understand strategic behavior.

In an econometric model that explicitly accounts for price endogeneity, we find that more-experienced drivers set lower prices and, controlling for price, sell more seats. We interpret this as evidence that prices and market outcomes on "sharing platforms" such as BlaBlaCar are determined differently than on electronic marketplaces such as eBay. Given that we find that more-experienced drivers earn more revenue, a leading explanation is that more-experienced drivers are better at revenue maximization. This is in line with results from AirBnB in Li, Moreno, and Zhang (2016), who show that experienced (professional) hosts are better than less experienced (non-professional) hosts at adjusting their price in response to demand fluctuations. Although all drivers on BlaBlaCar are non-professionals, they do not all have the same experience level, and we find evidence of learning to maximize revenues. This suggests that BlaBlaCar should assist inexperienced drivers, for example, using "heat maps" like displayed by Uber to their drivers to indicate the areas where they are more likely to earn higher revenues. BlaBlaCar could also recommend lower prices to newcomers than to experienced drivers.

Further, we find that driver demographics matter in interesting ways: our quantitatively strongest demographic predictor of demand is whether the driver has an Arabic name, which robustly reduces the driver's demand and revenue by a substantial amount. Our results concerning the outcomes of drivers with Arabic names suggests a role of policymakers in working with platforms such as BlaBlaCar to lessen the harm associated with (implicit or explicit) bias. Several suggestions along these lines are possible, all while keeping in mind the central role of trust among users of sharing platforms such as BlaBlaCar. First, drivers could be identified by user IDs (as done on eBay for example) without pictures, which would remove the identifiers that might reveal characteristics that might be subject to differential treatment. Second, BlaBlaCar could encourage or require automatic confirmation (which is similar to Instant Book on AirBnB); in conjunction with the removal of names and pictures, this instantaneous booking of trips removes the potential for screening on the part of drivers who might have preferences over certain characteristics of riders.

The rich nature of our BlaBlaCar data allows us to present a detailed analysis of market outcomes in an important type of peer-to-peer market. However, as usual with data from online markets, there are some features of the data that limit the questions we can ask. First, we do not observe information about the riders who are buying seats. Thus, we cannot measure the degree of homophily or social links between drivers and their passengers. Second, we have only a binary scale for ratings (positive or negative). Since the time of our data collection, BlaBlaCar has adopted a five-level reputation measure, which would be useful to verify our findings on the effects of experience on price and quantity demanded. Moreover, as the platform has matured, it will be interesting to analyze how the role of driver experience and demographics has evolved.

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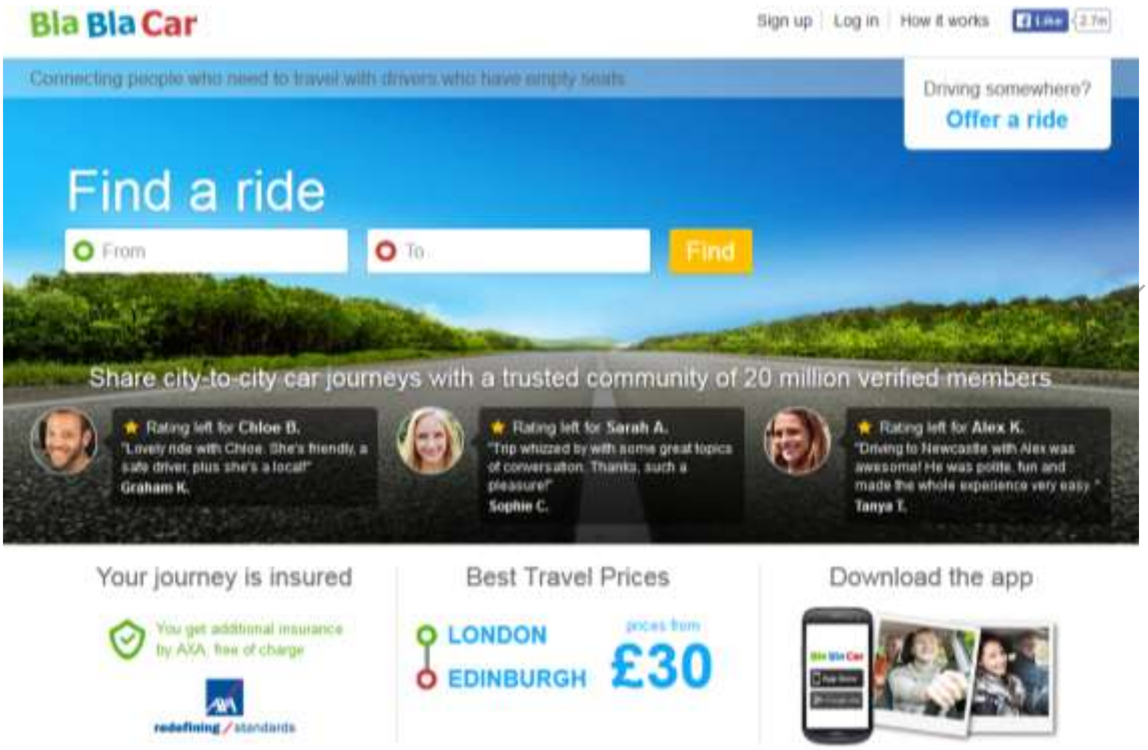
Figure 1: Screenshots of BlaBlaCar Website



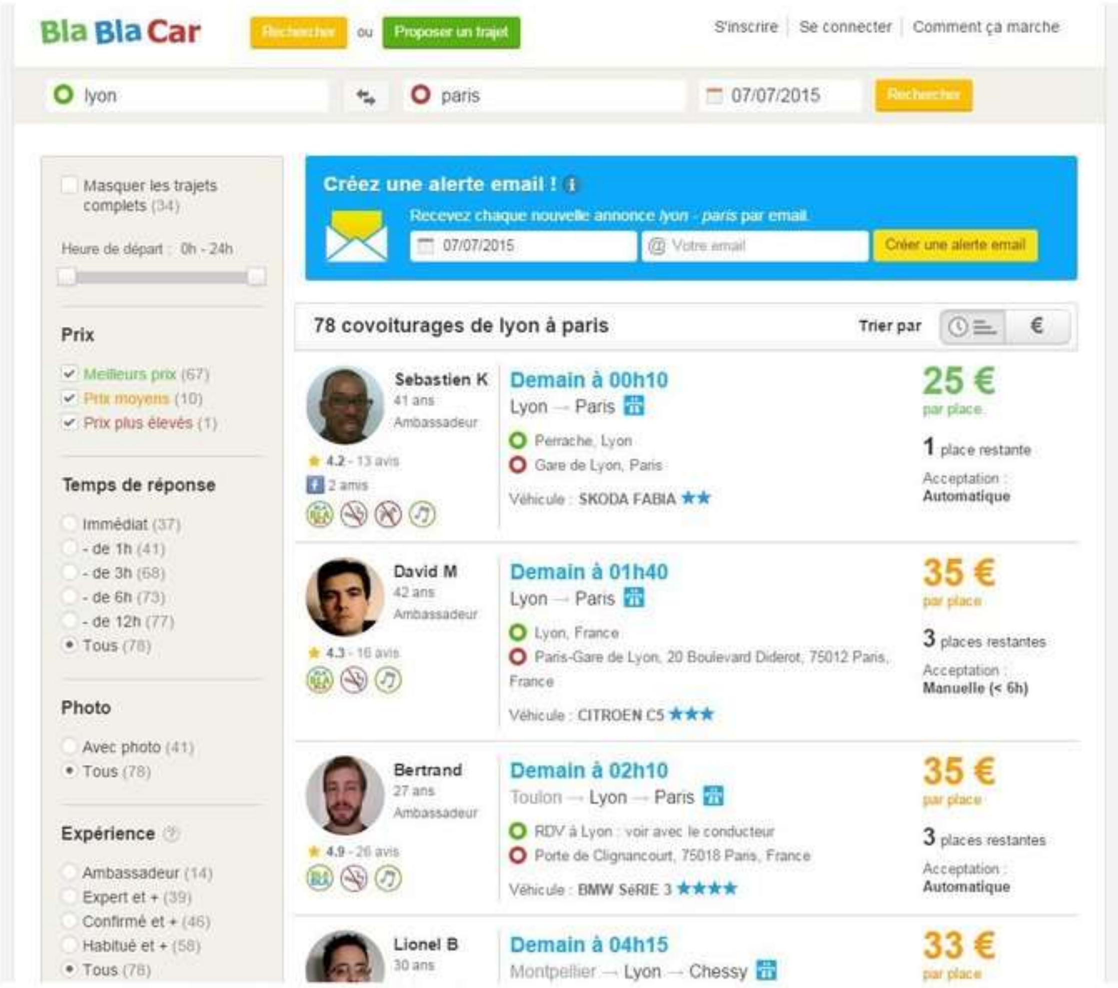

Bla Bla Car
Rechercher
ou
Proposer un trajet
S'inscrire
Se connecter
Comment ça marche
lyon
paris
07/07/2015
Rechercher
Masquer les trajets complets (34)
Heure de départ : 0h - 24h
Prix
Meilleurs prix (67)
Prix moyens (10)
Prix plus élevés (1)
Temps de réponse
Immédiat (37)
- de 1h (41)
- de 3h (68)
- de 6h (73)
- de 12h (77)
Tous (78)
Photo
Avec photo (41)
Tous (78)
Expérience
Ambassadeur (14)
Expert et + (39)
Confirmé et + (46)
Habitué et + (58)
Tous (78)
Créez une alerte email !
Recevez chaque nouvelle annonce lyon - paris par email.
07/07/2015
Votre email
Créer une alerte email
78 covoiturages de lyon à paris
Trier par
€
Sebastien K
41 ans
Ambassadeur
4.2 - 13 avis
2 amis
Demain à 00h10
Lyon → Paris
Perrache, Lyon
Gare de Lyon, Paris
Véhicule : SKODA FABIA
25 €
par place
1 place restante
Acceptation : Automatique
David M
42 ans
Ambassadeur
4.3 - 16 avis
Demain à 01h40
Lyon → Paris
Lyon, France
Paris-Gare de Lyon, 20 Boulevard Diderot, 75012 Paris, France
Véhicule : CITROEN C5
35 €
par place
3 places restantes
Acceptation : Manuelle (< 6h)
Bertrand
27 ans
Ambassadeur
4.9 - 26 avis
Demain à 02h10
Toulon → Lyon → Paris
RDV à Lyon : voir avec le conducteur
Porte de Clignancourt, 75018 Paris, France
Véhicule : BMW SéRIE 3
35 €
par place
3 places restantes
Acceptation : Automatique
Lionel B
30 ans
Demain à 04h15
Montpellier → Lyon → Chessy
33 €
par place

Table 1: BlaBlaCar's Driver Experience Levels

	Newcomer	Intermediate	Experienced	Expert	Ambassador
Profile completion		> 60%	> 70%	> 80%	> 90%
Number of ratings		1 rating	3 ratings	6 ratings	12 ratings
% positive ratings		> 60%	> 70%	> 80%	> 90%
Seniority		1 month	3 months	6 months	12 months

Table 2: Summary Statistics

Panel A: Unit of Observation = Driver	
Number of Same Trips	3.728
	(6.652)
Number of Other Trips	2.517
	(6.515)
Single-Trip Driver	0.547
	(0.498)
Feedback Quantity	8.366
	(18.987)
Feedback Quality	99.041
	(6.049)
Driver Status	2.659
	(1.446)
Car Class	2.261
	(1.053)
Age	36.009
	(13.293)
Female	0.401
	(0.490)
French Name	0.674
	(0.469)
Arabic Name	0.050
	(0.218)
Photo Shown	0.388
	(0.487)
Plays Music	0.555
	(0.497)
Allows Pets	0.088
	(0.283)
Allows Smoking	0.067
	(0.250)
Roundtrip	0.257
	(0.437)
Manual Confirmation	0.115
	(0.318)
N	294419

Panel B: Unit of Observation = Trip, Drivers Grouped by Driver Status						
	All	Newcomer	Intermediate	Experienced	Expert	Ambassador
Price	13.461	14.211	13.574	13.589	13.748	11.923
	(9.409)	(10.057)	(9.185)	(9.048)	(9.047)	(9.254)
Relative Price	-2.764	-2.162	-2.461	-2.659	-2.915	-3.801
	(5.914)	(6.013)	(5.724)	(5.686)	(5.719)	(6.219)
Seats Sold	1.122	0.964	1.074	1.117	1.160	1.346
	(1.510)	(1.418)	(1.470)	(1.494)	(1.515)	(1.641)
Fraction Sold	0.625	0.553	0.602	0.611	0.630	0.752
	(0.433)	(0.448)	(0.436)	(0.433)	(0.427)	(0.386)
All Seats Sold	0.537	0.464	0.508	0.516	0.535	0.682
	(0.499)	(0.499)	(0.500)	(0.500)	(0.499)	(0.466)
Avg. Price, Other Trips	11.139	10.889	10.920	11.090	11.383	11.473
	(7.872)	(8.349)	(7.878)	(7.691)	(7.637)	(7.590)
N	920789	232547	177267	148579	188407	173989

Notes: Standard deviations are in parentheses.

Table 3: Price Results

	(1) OLS	(2) IV
Avg. Price, Other Trips		0.010
		(0.000)***
Feedback Quantity	-0.000	-0.000
	(0.000)**	(0.000)**
Feedback Quality	0.005	0.005
	(0.001)***	(0.001)***
Intermediate	-0.159	-0.154
	(0.009)***	(0.009)***
Experienced	-0.277	-0.271
	(0.010)***	(0.010)***
Expert	-0.415	-0.410
	(0.010)***	(0.010)***
Ambassador	-0.442	-0.436
	(0.012)***	(0.012)***
Car Class=1	-0.374	-0.367
	(0.018)***	(0.018)***
Car Class=2	-0.200	-0.192
	(0.012)***	(0.012)***
Car Class=3	-0.017	-0.014
	(0.012)	(0.012)
Car Class=4	0.298	0.294
	(0.016)***	(0.016)***
Age	0.008	0.007
	(0.000)***	(0.000)***
Female	0.124	0.124
	(0.007)***	(0.007)***
French Name	0.007	0.031
	(0.008)	(0.009)***
Arabic Name	-0.191	-0.211
	(0.018)***	(0.018)***
Photo Shown	-0.022	-0.019
	(0.007)***	(0.007)***
Plays Music	-0.103	-0.100
	(0.007)***	(0.007)***
Allows Pets	-0.155	-0.153
	(0.011)***	(0.011)***
Allows Smoking	0.115	0.115
	(0.013)***	(0.013)***
Roundtrip	0.149	0.144
	(0.007)***	(0.007)***
Manual Confirmation	0.489	0.480
	(0.008)***	(0.008)***
N	920789	920789
First-Stage F Stat		1939.001

Notes: This table presents regressions where the dependent variable is the driver's price. Column (1) does not include the average-other-price instrument, while it is included in Column (2). The econometric specification is linear regression with trip fixed effects. For this and subsequent tables, standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For this and subsequent tables, all continuous variables (feedback quantity, feedback quality, age, departure time trend) are included in quadratic form. These and all results are shown as average marginal effects.

Table 4: Demand Results

	Fraction Sold		All Seats Sold	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Price	-0.002	-0.077	-0.003	-0.069
	(0.000)***	(0.002)***	(0.000)***	(0.002)***
Feedback Quantity	0.000	0.000	0.000	0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Feedback Quality	0.002	0.002	0.002	0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Intermediate	0.029	0.017	0.023	0.012
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Experienced	0.033	0.012	0.027	0.009
	(0.001)***	(0.002)***	(0.001)***	(0.002)***
Expert	0.043	0.012	0.036	0.008
	(0.001)***	(0.002)***	(0.001)***	(0.002)***
Ambassador	0.085	0.052	0.086	0.057
	(0.001)***	(0.002)***	(0.002)***	(0.002)***
Car Class=1	0.040	0.011	0.040	0.015
	(0.002)***	(0.003)***	(0.002)***	(0.003)***
Car Class=2	0.046	0.031	0.049	0.036
	(0.001)***	(0.002)***	(0.002)***	(0.002)***
Car Class=3	0.026	0.025	0.035	0.034
	(0.001)***	(0.002)***	(0.002)***	(0.002)***
Car Class=4	0.014	0.037	0.021	0.041
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Age	-0.001	0.000	-0.000	0.000
	(0.000)***	(0.000)	(0.000)***	(0.000)***
Female	0.018	0.028	0.043	0.051
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
French Name	0.062	0.062	0.027	0.028
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Arabic Name	-0.059	-0.074	-0.076	-0.089
	(0.002)***	(0.003)***	(0.002)***	(0.003)***
Photo Shown	0.006	0.004	0.007	0.006
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Plays Music	0.029	0.022	0.029	0.022
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Allows Pets	0.000	-0.012	0.000	-0.010
	(0.001)	(0.002)***	(0.002)	(0.002)***
Allows Smoking	-0.015	-0.006	-0.017	-0.009
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Roundtrip	-0.010	0.002	0.001	0.011
	(0.001)***	(0.001)	(0.001)	(0.001)***
Manual Confirmation	-0.477	-0.441	-0.582	-0.550
	(0.001)***	(0.002)***	(0.001)***	(0.002)***
N	920789	920789	920789	920789

Notes: This table presents demand regressions. Columns (1) and (3) do not use the average-other-price variable to instrument for price, while Columns (2) and (4) do. The dependent variable in Columns (1)-(2) is the driver's fraction of seats sold. The dependent variable in Columns (3)-(4) equals one when fraction sold equals one. The econometric specification is linear regression with trip fixed effects.

Table 5: Revenue Results

	(1)
Feedback Quantity	-0.005
	(0.001)***
Feedback Quality	0.076
	(0.006)***
Intermediate	0.777
	(0.051)***
Experienced	0.837
	(0.054)***
Expert	1.096
	(0.053)***
Ambassador	2.126
	(0.067)***
Car Class=1	0.990
	(0.095)***
Car Class=2	1.297
	(0.064)***
Car Class=3	0.577
	(0.063)***
Car Class=4	0.372
	(0.084)***
Age	-0.148
	(0.002)***
Female	-0.488
	(0.038)***
French Name	7.489
	(0.042)***
Arabic Name	-1.125
	(0.104)***
Photo Shown	0.082
	(0.036)**
Plays Music	0.581
	(0.037)***
Allows Pets	-0.449
	(0.060)***
Allows Smoking	-0.752
	(0.069)***
Roundtrip	-0.482
	(0.039)***
Manual Confirmation	-8.755
	(0.034)***
Seats in Car	8.151
	(0.012)***
N	920789

Notes: This table presents revenue regressions, where revenue is equal to the number of seats sold times the price. The econometric specification is a Tobit regression with trip fixed effects.

Table 6: Regression Results of Within-Driver Price Changes

	(1)
Feedback Quantity	-0.002
	(0.000)***
Feedback Quality	-0.001
	(0.002)
Intermediate	-0.187
	(0.017)***
Experienced	-0.286
	(0.018)***
Expert	-0.454
	(0.018)***
Ambassador	-0.460
	(0.022)***
N	276178

Notes: This table present within-driver price regression results, including all drivers with at least eleven listings. The econometric specification is the same as in Column (2) in Table 3, with the exception of the inclusion of driver fixed effects in addition to trip fixed effects. Due to the inclusion of driver fixed effects, time-invariant covariates are not included.

Table 7: Summary Statistics of Late-Tenure Listings Relative to Early-Tenure Relative Prices

	(1) *N*	(2) Price Range	(3) Listings
Price Category=1	2810	<-4.00	10.992
			(0.249)
Price Category=2	3702	[-4.00,-2.25)	10.894
			(0.216)
Price Category=3	3663	[-2.25,-1.00]	11.786
			(0.218)
Price Category=4	2814	>-1.00	11.337
			(0.248)

Notes: These summary statistics include all drivers with at least eleven listings who we first observe as a newcomer (status of one). Shown are price categories based on relative prices set during the first ten listings of each driver's tenure during our sample period. Listings are the count of late-tenure listings (i.e., listings eleven and later). Price categories are determined by quartiles of relative prices (i.e., the driver's price minus the recommended price).

Table 8: Summary Statistics of Late-Tenure Relative Prices Relative to Early-Tenure Sales

	(1) *N*	(2) Sales Range	(3) Initial Price	(4) Later Price	(5) Price Change
Sales Category=1	139	=0.00	-1.973	-2.413	-0.440
			(0.170)	(0.084)	(0.149)
Sales Category=2	4998	(0.00,0.50]	-2.1196	-2.317	-0.121
			(0.029)	(0.017)	(0.033)
Sales Category=3	7071	[0.50,1.00)	-2.776	-2.820	-0.044
			(0.023)	(0.013)	(0.024)
Sales Category=4	781	=1.00	-3.991	-3.541	0.450
			(0.141)	(0.112)	(0.236)

Notes: These summary statistics include all drivers with at least eleven listings who we first observe as a newcomer (status of one). Shown are sales categories based on the driver's average proportion of seats sold during her first ten listings during our sample period. Prices are the predicted relative price charged by drivers across their tenure on the platform, using the regression model from Table 3. Initial price is the average relative price measured for drivers' first observed trip, later price is the average relative price measured for drivers' who have had the average number of trips (17.2), and price change is the difference from initial price to later price.

Appendix A: Additional Figures and Tables

Figure A1: Nonlinearities in the Effect of Age on Price

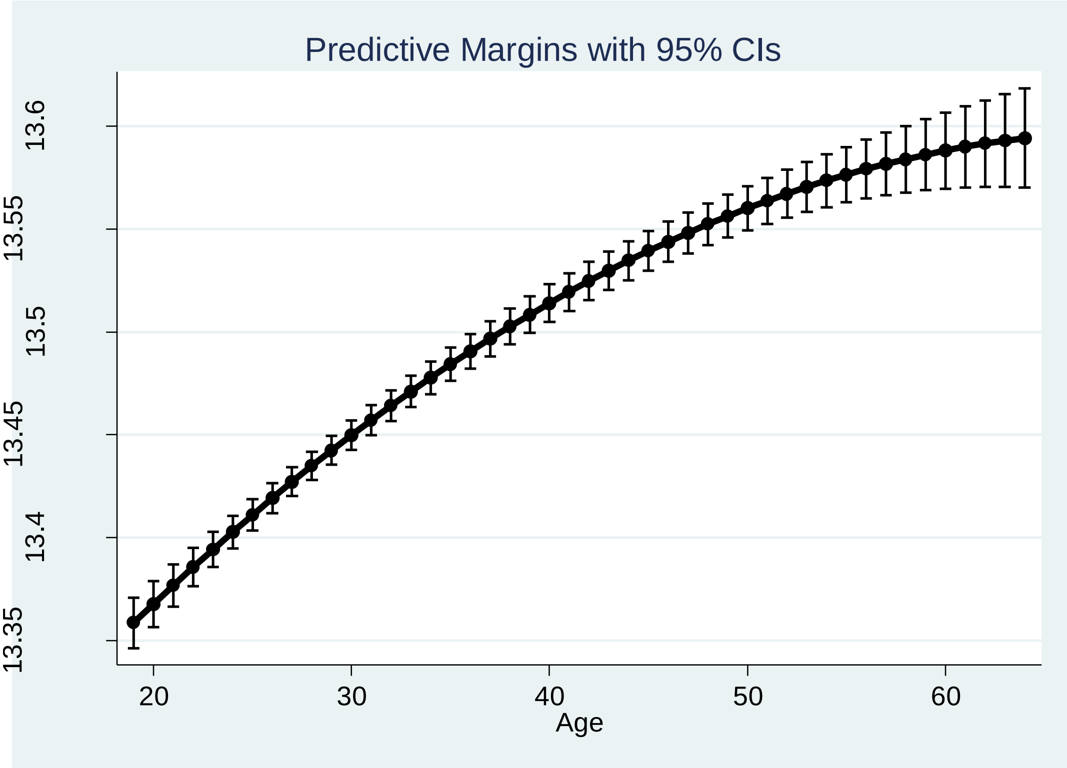


Figure A2: Nonlinearities in the Effect of Age on Pr(Sale)

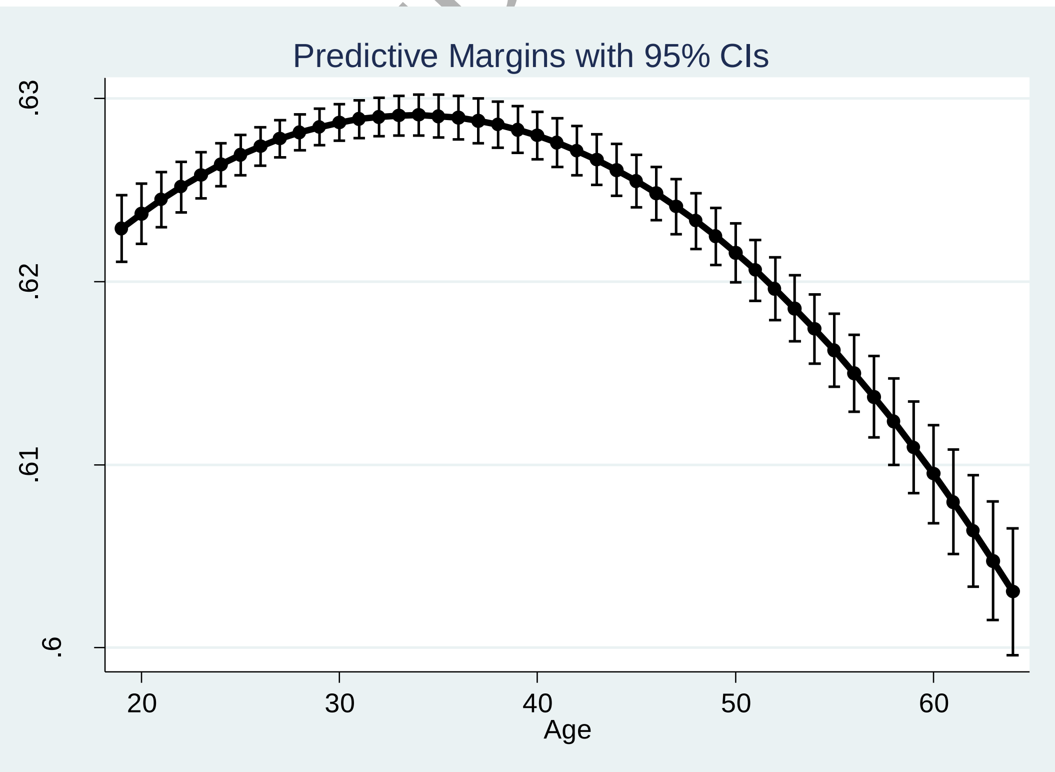


Table A1: Summary Statistics by Trip

	N	Price Mean	StdDev	P1	Median	P99	Fraction Sold	Distance (km)
Aix Avignon	14505	5.179	1.531	2	5	10	0.604	81
Amiens Beauvais	3400	4.274	1.316	2	4	7	0.659	66
Angers LeMans	22514	6.184	1.378	3	6	10	0.568	97
Besancon Dijon	3026	5.885	2.170	2	6	10	0.468	93
Bordeaux Nantes	36577	21.165	2.350	15	21	27	0.624	353
Brest SaintBrieuc	7899	8.060	1.700	4	8	13	0.442	144
Caen Rennes	22892	10.979	1.742	7	11	15	0.504	185
Clermont Lyon	28908	12.362	1.984	8	13	17	0.560	166
Dijon Besancon	3217	5.881	2.033	2	6	12	0.454	93
Grenoble Lyon	23893	6.847	1.465	4	7	10	0.502	105
LeHavre Caen	7978	5.820	1.094	3	6	9	0.529	96
LeMans Tours	14096	5.650	1.435	3	6	10	0.552	102
Lens Paris	44913	14.309	1.680	10	15	19	0.588	199
Lille Paris	49450	14.559	1.615	10	15	20	0.602	220
Limoge Toulouse	19734	17.998	3.020	12	18	25	0.548	291
Lyon Grenoble	24021	6.886	1.669	4	7	10	0.494	105
Lyon Paris	48316	29.145	3.419	20	30	38	0.666	466
Marseille Nice	5162	13.223	3.156	6	13	21	0.385	198
Metz Nancy	30958	3.547	0.995	1	4	6	0.938	60
Montpellier Marseille	15327	10.917	2.145	7	11	16	0.511	169
Nancy Strasbourg	4326	9.185	2.306	3	10	17	0.458	156
Nantes Bordeaux	36524	21.133	2.275	15	21	26	0.614	353
Nantes Rennes	51978	5.870	1.400	4	6	9	0.507	113
Nice Toulon	2004	10.885	2.782	7	10	17	0.299	150
Nimes Montpellier	89098	3.065	0.817	1	3	5	0.971	58
Orleans Paris	24963	8.266	2.460	4	8	12	0.549	133
Paris Brest	17063	36.140	3.717	25	37	45	0.712	591
Paris Caen	17997	15.002	1.947	10	15	20	0.524	234
Paris Lyon	46706	29.101	3.680	20	30	38	0.658	466
Paris Marseille	5282	47.337	9.809	19	50	71	0.608	774
Pau Bordeaux	12415	13.918	2.595	9	14	20	0.465	218
Perpignan Narbonne	22578	4.205	1.277	1	4	7	0.759	66
Reims Troyes	9190	8.082	1.965	5	8	13	0.466	127
Rennes Brest	11358	12.758	2.531	8	12	19	0.458	243
Rouen Paris	13462	8.734	1.501	5	9	12	0.488	136
SaintEtienne Clermont	35504	22.676	10.183	3	23	49	0.577	144
Strasbourg Colmard	8192	4.314	1.162	1	4	8	0.732	76
Toulon Aix	10502	5.448	1.771	1	6	10	0.540	84
Toulouse Bordeaux	47913	15.111	2.019	10	15	20	0.539	245
Tours Paris	26948	15.434	2.850	10	15	21	0.628	240
Total	920789	13.461	9.409	2	12	40	0.625	

Notes: This table presents trip-level summary statistics. Shown are the number of observations in the data by trip, summary statistics for price, mean fraction of seats sold, fraction of seats sold, and the distance between the two cities in kilometers. The statistics shown for price are the mean, standard deviation, 1st percentile, median, and 99th percentile.

Table A2: Tabulation of Relative Price

	Frequency	Percent	Cumulative
>-10	53757	5.84	5.84
-10	8325	0.90	6.74
-9	11164	1.21	7.95
-8	15242	1.66	9.61
-7	22794	2.48	12.09
-6	36176	3.93	16.01
-5	45724	4.97	20.98
-4	81057	8.80	29.78
-3	95614	10.38	40.17
-2	138288	15.02	55.19
-1	169677	18.43	73.61
0	119305	12.96	86.57
1	34929	3.79	90.36
2	25910	2.81	93.18
3	21131	2.29	95.47
4	12516	1.36	96.83
5	8541	0.93	97.76
6	5921	0.64	98.40
7	3918	0.43	98.83
8	1906	0.21	99.03
9	1082	0.12	99.15
10	745	0.08	99.23
<10	7067	0.77	100.00
Total	920789	100.00	

Notes: This table presents a tabulation of drivers' prices minus the recommended price, that is, the relative price.

Table A3: Regression Results of Departure Characteristics

	(1) Price	(2) Fraction Sold	(3) All Seats Sold
Departure=Monday	-0.099	-0.056	-0.059
	(0.011)***	(0.002)***	(0.002)***
Departure=Tuesday	-0.123	-0.098	-0.105
	(0.013)***	(0.002)***	(0.002)***
Departure=Wednesday	-0.071	-0.093	-0.103
	(0.013)***	(0.002)***	(0.002)***
Departure=Thursday	0.021	-0.058	-0.064
	(0.012)*	(0.002)***	(0.002)***
Departure=Friday	-0.037	-0.022	-0.025
	(0.009)***	(0.001)***	(0.001)***
Departure=Saturday	0.075	0.004	0.002
	(0.011)***	(0.002)***	(0.002)
Departure=[6AM,12PM]	0.014	0.055	0.070
	(0.023)	(0.003)***	(0.003)***
Departure=[12PM,6PM]	-0.064	0.054	0.068
	(0.023)***	(0.003)***	(0.003)***
Departure=[6PM,12AM]	-0.209	0.011	0.022
	(0.024)***	(0.003)***	(0.004)***
Departure Time Trend	-0.004	-0.000	0.000
	(0.000)***	(0.000)	(0.000)***
N	920789	920789	920789

Notes: This table presents additional covariates from the earlier price and demand regressions. Column (1) of Table 5 present results from the same regression as in Column (2) of Table 3, respectively. Columns (2) and (3) of Table 5 present results from the same regressions as in Columns (2) and (4) of Table 4, respectively. These results are from the exact same regression, broken into multiple tables for ease of presentation.

Table A4: Additional Regression Results for Price

	(1)	(2)	(3)	(4)
Avg. Price, Other Trips				0.010
				(0.000)***
Feedback Quantity			-0.000	-0.000
			(0.000)**	(0.000)**
Feedback Quality			0.005	0.005
			(0.001)***	(0.001)***
Intermediate	-0.211	-0.166	-0.159	-0.154
	(0.009)***	(0.009)***	(0.009)***	(0.009)***
Experienced	-0.347	-0.285	-0.277	-0.271
	(0.010)***	(0.010)***	(0.010)***	(0.010)***
Expert	-0.499	-0.416	-0.415	-0.410
	(0.009)***	(0.009)***	(0.010)***	(0.010)***
Ambassador	-0.549	-0.414	-0.443	-0.437
	(0.010)***	(0.010)***	(0.012)***	(0.012)***
Age		0.009	0.008	0.007
		(0.000)***	(0.000)***	(0.000)***
Female		0.072	0.123	0.124
		(0.007)***	(0.007)***	(0.007)***
French Name		-0.009	-0.001	0.022
		(0.008)	(0.008)	(0.009)**
Arabic Name		-0.196	-0.216	-0.239
		(0.018)***	(0.018)***	(0.018)***
Photo Shown		-0.027	-0.022	-0.019
		(0.007)***	(0.007)***	(0.007)***
Plays Music		-0.099	-0.103	-0.100
		(0.007)***	(0.007)***	(0.007)***
Allows Pets		-0.171	-0.156	-0.154
		(0.011)***	(0.011)***	(0.011)***
Allows Smoking		0.084	0.115	0.115
		(0.013)***	(0.013)***	(0.013)***
Roundtrip		0.150	0.149	0.144
		(0.007)***	(0.007)***	(0.007)***
Manual Confirmation		0.491	0.489	0.480
		(0.008)***	(0.008)***	(0.008)***
Car Class=1			-0.375	-0.368
			(0.018)***	(0.018)***
Car Class=2			-0.200	-0.192
			(0.012)***	(0.012)***
Car Class=3			-0.016	-0.013
			(0.012)	(0.012)
Car Class=4			0.298	0.293
			(0.016)***	(0.016)***
N	920789	920789	920789	920789

Notes: This table presents additional specifications for price. Columns (3) and (4) match Columns (1) and (2) from Table 3.

Table A5: Demand Regression with only Multiple-Trip Drivers

	Fraction Sold		All Seats Sold	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Price	-0.002	-0.025	-0.002	0.006
	(0.000)***	(0.002)***	(0.000)***	(0.002)***
Feedback Quantity	0.000	0.000	0.000	0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Feedback Quality	0.002	0.002	0.002	0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Intermediate	0.023	0.019	0.018	0.019
	(0.001)***	(0.001)***	(0.001)***	(0.002)***
Experienced	0.024	0.017	0.021	0.023
	(0.001)***	(0.002)***	(0.002)***	(0.002)***
Expert	0.034	0.024	0.030	0.033
	(0.001)***	(0.002)***	(0.002)***	(0.002)***
Ambassador	0.081	0.070	0.088	0.092
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Car Class=1	0.036	0.027	0.037	0.040
	(0.002)***	(0.003)***	(0.003)***	(0.003)***
Car Class=2	0.043	0.038	0.049	0.051
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Car Class=3	0.024	0.023	0.037	0.037
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Car Class=4	0.016	0.022	0.030	0.027
	(0.002)***	(0.002)***	(0.002)***	(0.003)***
Age	-0.002	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Female	0.002	0.005	0.025	0.024
	(0.001)**	(0.001)***	(0.001)***	(0.001)***
French Name	0.135	0.132	0.116	0.117
	(0.001)***	(0.001)***	(0.002)***	(0.002)***
Arabic Name	-0.047	-0.053	-0.065	-0.063
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Photo Shown	0.005	0.005	0.007	0.007
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Plays Music	0.025	0.023	0.024	0.025
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Allows Pets	-0.001	-0.005	-0.001	0.000
	(0.002)	(0.002)***	(0.002)	(0.002)
Allows Smoking	-0.015	-0.013	-0.019	-0.020
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Roundtrip	-0.013	-0.009	0.001	-0.000
	(0.001)***	(0.001)***	(0.001)	(0.001)
Manual Confirmation	-0.435	-0.423	-0.542	-0.546
	(0.001)***	(0.001)***	(0.001)***	(0.002)***
N	725202	725202	725202	725202

Notes: This table follows Table 4 but only includes multiple-trip drivers (i.e., drivers who were observed with listings between more than one pair of cities).

Appendix B: Robustness Checks Using Alternative Instruments

In this appendix, we introduce two strategies for constructing alternative instruments and demonstrate the robustness of the main results. First, we use the time series dimension of the data and look at drivers who offered listings of the trip in question during the week prior to the week in question. If the driver in question listed the trip in the prior week also, she is excluded from the construction of these instruments. Specifically, we use the one week lag of characteristics of other drivers on the same trip in the prior week.

The instrument we use is the average fraction of orange or red prices (i.e., not green prices) for the prices set by other drivers on the same trip in the prior week. We investigated a number of alternative instruments but find that they do not pass validity tests (i.e., there is evidence that they are weak). While this type of intertemporal instrument is common in empirical microeconomics, we do not find that our covariates are particularly strong in these data. To provide evidence of the robustness of our results, we include the strongest of such instruments: average fraction of orange or red prices. Given concerns over weak instruments, we include this lagged instrument along with our preferred instrument: the average-other-price instrument. The results are in Table B1. The first column reproduces Column (2) from Table 3 for comparison.

[Insert Table B1]

The second strategy for constructing alternative instruments is to use a similar strategy used for the average-other-price instrument of exploiting the panel nature of the data. Here we use the average characteristics of other drivers than the driver in question's modal trip (other than the trip in question) during the same week. First, we construct the average feedback quantity of other drivers on the driver in question's modal trip in the same week. Second, we construct the average fraction of orange or red prices (i.e., not green prices) on the modal trip in the same week. The results are in Table B2. The first column reproduces Column (1) from Table 3 for comparison.

[Insert Table B2]

In both tables, the main results are highly robust. First, driver experience matters more than driver reputation, but both positively affect sales, with the largest effect coming from the move to ambassador status (i.e., the highest level of experience). Second, driver demographics matter, with females and drivers with French names selling more seats and drivers with Arabic names selling fewer seats. The price elasticity itself is robustly statistically significantly negative and of similar magnitude across each column.

These results are intended to demonstrate the robustness of our analysis to alternative approaches to controlling for the endogeneity of price in the estimation of the effects of driver characteristics (experience and demographics) on demand. We conclude that all of the results carry over.

Table B1: Robustness Checks Using First Set of Alternative Instruments

	(1)	(2)
Price	-0.077	-0.060
	(0.002)***	(0.002)***
Feedback Quantity	0.000	0.000
	(0.000)***	(0.000)***
Feedback Quality	0.002	0.002
	(0.000)***	(0.000)***
Intermediate	0.017	0.019
	(0.001)***	(0.001)***
Experienced	0.012	0.017
	(0.002)***	(0.001)***
Expert	0.012	0.019
	(0.002)***	(0.002)***
Ambassador	0.052	0.059
	(0.002)***	(0.002)***
Car Class=1	0.011	0.018
	(0.003)***	(0.002)***
Car Class=2	0.031	0.034
	(0.002)***	(0.002)***
Car Class=3	0.025	0.026
	(0.002)***	(0.002)***
Car Class=4	0.037	0.031
	(0.002)***	(0.002)***
Age	0.000	-0.000
	(0.000)	(0.000)**
Female	0.028	0.026
	(0.001)***	(0.001)***
French Name	0.062	0.061
	(0.001)***	(0.001)***
Arabic Name	-0.074	-0.072
	(0.003)***	(0.002)***
Photo Shown	0.004	0.005
	(0.001)***	(0.001)***
Plays Music	0.022	0.023
	(0.001)***	(0.001)***
Allows Pets	-0.012	-0.009
	(0.002)***	(0.002)***
Allows Smoking	-0.006	-0.008
	(0.002)***	(0.002)***
Roundtrip	0.002	-0.001
	(0.001)	(0.001)
Manual Confirmation	-0.441	-0.449
	(0.002)***	(0.001)***
N	920789	919257
First-Stage F Stat	1939.001	1079.877

Notes: These robustness checks present alternative instruments with fraction of seats sold as the dependent variable. Column (1) reproduces Column (2) from Table 3 for comparison. This alternative instrument is based on the one week lag of average characteristics of other drivers on the same trip (excluding the driver in question), as described in the paper. Column (2) includes the average-other-price instrument from Column (2) from Table 3 and the average fraction of orange or red prices (i.e., not green prices) for other drivers on the trip in the prior week.

Table B2: Robustness Checks Using Second Set of Alternative Instruments

	(1)	(2)
Price	-0.077	-0.042
	(0.002)***	(0.010)***
Feedback Quantity	0.000	0.000
	(0.000)***	(0.000)***
Feedback Quality	0.002	0.002
	(0.000)***	(0.000)***
Intermediate	0.017	0.023
	(0.001)***	(0.002)***
Experienced	0.012	0.022
	(0.002)***	(0.003)***
Expert	0.012	0.027
	(0.002)***	(0.005)***
Ambassador	0.052	0.067
	(0.002)***	(0.005)***
Car Class=1	0.011	0.025
	(0.003)***	(0.004)***
Car Class=2	0.031	0.038
	(0.002)***	(0.003)***
Car Class=3	0.025	0.026
	(0.002)***	(0.002)***
Car Class=4	0.037	0.026
	(0.002)***	(0.004)***
Age	0.000	-0.000
	(0.000)	(0.000)***
Female	0.028	0.023
	(0.001)***	(0.002)***
French Name	0.062	0.061
	(0.001)***	(0.001)***
Arabic Name	-0.074	-0.068
	(0.003)***	(0.003)***
Photo Shown	0.004	0.005
	(0.001)***	(0.001)***
Plays Music	0.022	0.025
	(0.001)***	(0.001)***
Allows Pets	-0.012	-0.006
	(0.002)***	(0.002)***
Allows Smoking	-0.006	-0.010
	(0.002)***	(0.002)***
Roundtrip	0.002	-0.004
	(0.001)	(0.002)**
Manual Confirmation	-0.441	-0.458
	(0.002)***	(0.005)***
N	920789	920789
First-Stage F Stat	1939.001	36.942

Notes: These robustness checks present alternative instruments with fraction of seats sold as the dependent variable. Column (1) reproduces Column (2) from Table 4 for comparison. These alternative instruments are based on the average characteristics of other drivers on the driver's modal trip (excluding the driver in question), as described in the paper. Column (2) includes two such instruments: average feedback quantity and average fraction of orange or red prices (i.e., not green prices), constructed from other drivers on the driver in question's modal trip in the same week.

Appendix C: Analysis of the Use of Manual Confirmation

In this appendix, we present a regression analysis of manual confirmation. We find in the main analyses that manual confirmation is one of the strongest predictors of demand, reducing demand and revenue dramatically. As a result, we seek to understand which types of drivers use this option.

Appendix Table C1 displays the characteristics of the drivers choosing manual confirmation. Drivers with less experience and feedback are more likely to choose this option. Younger and male drivers, as well as drivers with an Arabic-sounding name tend to avoid manual confirmation (i.e., use "instant book"). The choice of manual confirmation can reflect a lack of experience with the platform, but also some taste-based screening from female and older drivers who may prefer to know with whom they will travel (even at the cost of sales).

Table C1: Manual Confirmation Results

	(1)
Feedback Quantity	-0.001
	(0.000)***
Feedback Quality	-0.000
	(0.000)
Intermediate	-0.026
	(0.001)***
Experienced	-0.026
	(0.001)***
Expert	-0.038
	(0.001)***
Ambassador	-0.058
	(0.002)***
Car Class=1	-0.017
	(0.002)***
Car Class=2	-0.031
	(0.002)***
Car Class=3	-0.028
	(0.001)***
Car Class=4	-0.014
	(0.002)***
Age	-0.002
	(0.000)***
Female	0.019
	(0.001)***
French Name	0.005
	(0.001)***
Arabic Name	-0.023
	(0.002)***
Photo Shown	-0.025
	(0.001)***
Plays Music	0.008
	(0.001)***
Allows Pets	-0.008
	(0.001)***
Allows Smoking	-0.001
	(0.002)
Roundtrip	0.008
	(0.001)***
N	920789

Notes: This table presents manual confirmation regressions. The dependent variable equals one if the driver chose to require manual confirmation on the trip, rather than allowing instant booking. The econometric specification is linear regression with trip fixed effects.