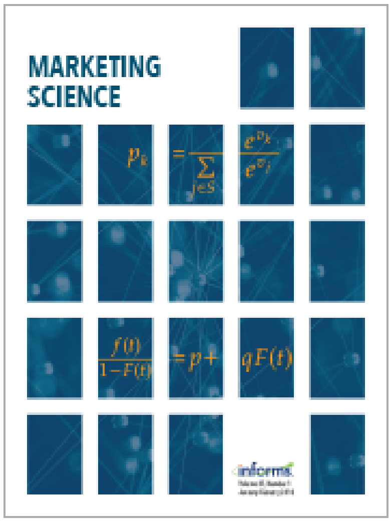

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Mobile Hailing Technology and Taxi Driving Behaviors

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Abstract. This paper investigates the impact of mobile hailing technology on taxi driving behaviors. A controversial feature of mobile hailing applications in China is the disclosure of not only pickup locations but also drop-off destinations before drivers accept offers. It provides taxi drivers two different mechanisms to improve their hourly earnings: reducing cruising time and selecting more profitable trips. We examine 3.6-terabyte minute-by-minute geolocation data of 2,106 single-shift drivers in Beijing. A modified change-point model is proposed to infer the adoption decisions and estimate the changes in driving behaviors. We show that mobile hailing technology adoption is associated with an average increase of 6.8% in hourly earnings, equivalent to an extra CNY 750 monthly income. A typical taxi driver greatly improves hourly earnings through trip selection in favor of longer trips rather than aiming for cruising-time reduction. We find that the relative importance of cruising-time reduction and trip selection depends on driver skills and market conditions. We do not find market expansions on the number of trips or working hours, but rather a redistribution of realized trips toward long distances.

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Keywords: mobile hailing apps • taxi industry • technology adoption • Didi

1. Introduction

Recent innovation in mobile technology has changed the way the traditional taxi industry operates. The new mobile hailing technology reveals local demand to the app-using drivers and shares the location data of waiting passengers. Detailed local demand information has the potential to reduce taxi drivers' cruising time between rides and improve their hourly earnings. The value of detailed customer data has been well documented in marketing research on targeting (Goldfarb and Tucker 2011). However, there is also an emerging stream of research on the unintended consequences of revealing customers' private information (Acquisti et al. 2016, Kim et al. 2019). For example, Edelman et al. (2017) show that in the Airbnb online rental market, the applicants' disclosed personal information such as their name is used against their application. In the marketplace, quite a few mobile hailing applications reveal pickup and drop-off locations to taxi drivers before they commit to a trip. This offers a possibility for taxi drivers to select larger-fare long trips. Despite the potential significance, there is only scarce marketing literature studying the impact of mobile hailing technology adoption on taxi driving behaviors.

Driving a cab is like managing a small business, as drivers have the flexibility to decide when, where, and how to work. It requires high skill in choosing the cruising areas of a city and determining hot-spot pickup locations at different times within a day. A taxicab driver in London, for example, needs to commit to memory 25,000 streets encompassing at least 20,000 landmarks (Chibber 2015). Taxi drivers' hourly earnings are the fares earned divided by the sum of the time spent driving passengers and cruising in search of new passengers. Mobile-app-adopting taxi drivers can take two distinct approaches to improve their hourly earnings: They can reduce the cruising time between trips with the help of mobile hailing technology, which helps fill the information gap, reduce the search friction, and make it more efficient for taxi drivers to locate waiting passengers. Alternatively, taxi drivers can increase their hourly earnings by engaging in trip selection in favor of longer and larger-fare journeys. Given the same cruising time, a longer trip brings in more earnings, increases the relative ratio of driving over cruising time, and effectively boosts the productivity measure of hourly earnings. Little is known about whether taxi drivers' hourly earnings may increase after adopting mobile hailing technology. More importantly, the question remains as to whether the increase is due to cruising-time reduction or trip selection, as the two mechanisms would lead to diverging regulatory implications of the mobile innovation.

Taxi drivers were accused of rejecting smaller-fare trips or journeys to certain destinations in the past. Although many cities have continuously made efforts to reduce the taxi trip rejection rate, the prevalence and design of new mobile hailing technology raise the possibility of erasing the achieved gains in eliminating trip selection and improving consumer welfare. The issue of cherry-picking potentially can resurface. Mobile hailing applications make different rules for revealing drop-off locations. For example, the Uber driver app does not reveal a passenger's destination until a driver picks up the passenger, to avoid cherry-picking. In contrast, almost all the mobile hailing apps in China provide taxi drivers with the passengers' pickup as well as drop-off locations, and this has largely been the case ever since these apps were launched on the market in 2013. This design feature spurred an outcry to block passengers' destinations. There is widespread concern that it has become even more difficult to find a cab for short trips after the launch of mobile hailing technology (Langfitt 2014). Most recently, in December 2017, four years after the introduction of mobile hailing applications in China, regulators in a few cities such as Shanghai ordered the apps to block passengers' destinations before orders are accepted to prevent this cherry-picking (CGTN 2017).

It is also unclear whether taxi drivers expand serving areas after adoption of the mobile hailing technology. Taxi drivers may be willing to explore new areas, as the technology is of help in locating local demand. However, the revealed destinations allow them to avoid particular areas with hard-to-find return trips or areas prone to a high proportion of less profitable trips. With an increase in hourly earnings, taxi drivers may take fewer trips and reduce working hours in line with income-targeting efforts (Camerer et al. 1997). To provide further regulatory guidance on mobile hailing innovation, there is a call for empirical evidence on the driving behavior changes before and after the adoption of mobile hailing technology.

This paper investigates the impact of mobile hailing technology on multiple driving behaviors, including cruising time between trips, trip distance, cruising area concentration, daily number of trips, and daily working hours. Our goal is to investigate whether mobile hailing technology adoption affects taxi drivers' hourly earnings and in which ways the improvement in hourly earnings is achieved. We aim to decompose the gains in taxi drivers' hourly earnings into cruising-time reduction, trip-distance increase, cruising area concentration, increase in the daily number of trips, and reduction of daily working hours. If taxi drivers engage in trip selection in favor of longer trips, it will hurt the welfare of short-trip riders and make mobile hailing applications less attractive to them. Regulation regarding information disclosure would be needed in this case. On the contrary, if the gain in hourly earnings is primarily the result of cruising-time reduction and an increase in number of trips, mobile hailing technology will motivate driver labor supply, expand the market, and increase social welfare. Driving skills before adoption and market conditions can moderate the relative importance of the two mechanisms. For example, low-skill drivers who previously idled for long periods searching for passengers may be better off reducing cruising time rather than attempting to control trip selection.

Our research context is the introduction of mobile hailing technology in the taxi industry in Beijing, China. All the mobile hailing applications introduced in Beijing in the time window (2013–2014) reveal riders' pickup as well as drop-off locations before taxi drivers accept requests. A few features make the context particularly attractive to our study. The regulation on mobile hailing technology limited access to licensed taxi drivers only. Entry of new drivers was restricted such that the supply of taxi drivers was stable during our observation window. Meanwhile, surge pricing had yet to be implemented by the local mobile hailing apps, and Uber-type ride-sharing services were not yet available during the observation window. This ensures that the driving behavior changes are not confounded with the entry of different forms of competition or the introduction of surge pricing.

We obtained 3.6-terabyte minute-by-minute geolocation data of 2,106 randomly sampled single-shift drivers in Beijing. The global positioning system (GPS) trajectories were tracked over an 18-month period, during which mobile hailing technology was introduced. The data include information on each driver's GPS coordinates, driving directions, driving speed, and in-service state at each minute interval. A challenge in the data is that we do not observe each individual driver's adoption of mobile hailing technology. To overcome this challenge, we build a modified change-point model that detects the unobserved adoption decision via observed changes in driving behaviors (Barry and Hartigan 1993, Chib 1998, Fader et al. 2004, Netzer et al. 2008, Schweidel and Fader 2009, Gopalakrishnan et al. 2017). We make an assumption that the adoption of mobile hailing technology will affect changes in at least one of the driving behaviors, including cruising time between trips, trip distance, cruising area concentration, daily number of trips, and daily working hours. We augment the detection of the adoption decision with surveyed adoption data, and we control for potential selection and endogeneity issues in the Bayesian Markov chain Monte Carlo (MCMC) estimation framework. A synthetic control method is used to cross-validate the results based on the change-point model.

We find evidence that mobile hailing technology adoption is associated with changes in multiple dimensions of driving behaviors. In the beginning, an average taxi driver was able to reduce cruising time between trips and slightly select in favor of longer trips. Idle-time reduction and trip selection contribute to an increase in hourly productivity. Meanwhile, the new technology allows taxi drivers to work significantly fewer hours in a day. Over time, the idle-time reduction attenuates. In fact, when the market adoption rate approaches 40%, an average taxi driver who has adopted this technology spends about the same amount of time searching for passengers as he did before adopting the mobile hailing apps. In contrast, there is a significant increase in trip distance as the market adoption rate increases.

We quantify the impact of adoption on taxi drivers' hourly earnings. The results show that mobile hailing technology adoption is associated with an average 6.8% increase in hourly earnings, equivalent to approximately CNY 750 monthly income gain. For an average taxi driver, the majority of this hourly earnings increase comes from trip selection in favor of longer trips (6.2% out of 6.8%). Only a very small amount of hourly earnings change is due to the reduction in cruising time between trips (0.5% out of 6.8%). Interestingly, we find that the relative importance of the two mechanisms of hourly earnings improvement depends on driver skills and market conditions. Highly skilled drivers who were able to efficiently cruise and locate trips could probably hit the ceiling of cruising-time reduction; as a result, they use mobile hailing applications primarily to look for longer trips to improve the driving-over-cruising ratio and increase hourly earnings. Low-skill drivers who had trouble locating trips efficiently prior to app adoption take advantage of the notification of local demand with the mobile hailing applications. Their hourly earnings increase comes mainly (70%) from the cruising-time reduction in thick markets with abundant demand. However, the sparse local demand in thin markets limits the information role of mobile hailing applications, and low-skill drivers rely on both cruising-time reduction and selection of longer trips to achieve an increase in hourly earnings.

Beyond taxi drivers' behavior changes, we provide indirect evidence on rider welfare. We show that there is no market expansion effect of the introduction of mobile hailing technology in the sense that the number of realized trips did not increase. Instead, we see a redistribution of the realized trips toward long trips, implying that the full disclosure of pickup as well as drop-off locations could be a double-edged sword. It increases the technology-adopting taxi drivers' earnings at the cost of a loss of welfare for short-trip riders.

We suggest that the remedies are not difficult or burdensome. Simply waiting to reveal a rider's destination until a trip is accepted is a direct and feasible choice. Our results echo the recent reactions by a few local regulators that ban the disclosure of trip destinations to drivers before they accept an offer.

2. Literature

This paper is broadly related to three streams of literature. We first discuss the literature on the performance impact of information technology (IT) adoption. We then relate our research to the sales force management literature in customer selection. Next, we discuss the relevant research on the taxi industry.

Early research on the relationship between IT and business performance failed to reject the null hypothesis that computer investment has no impact on productivity (Loveman 1993). Brynjolfsson and Hitt (1996) use firm-level survey data and demonstrate a significant contribution of computer investment to annual sales. Recent work looks at the trend toward IT adoption decisions and focuses on what types of firms are more likely to adopt a new technology. Sudhir and Talukdar (2015) investigate the productivity–transparency trade-off in emerging markets. Their results show that computer technology adoption is lower when firms are motivated to avoid transparency with tax implications. Economides and Jeziorski (2017) study the adoption of mobile technology in financial services (mobile money) in developing countries. Using demand estimation, they find that the major motivation to use mobile money is to ameliorate the crime-related risks. We take a similar approach as Economides and Jeziorski (2017) to understand whether drivers' hourly earnings improve after the adoption of mobile hailing technology and in which ways the improvement occurs.

One of the potential consequences of revealing riders' drop-off locations is customer selection. However, customer selection is not a behavior unique to the taxi industry. A connection can be made to the sales force management literature. It is documented in the literature that salespeople have incentives to engage in customer selection, which may not be necessarily aligned with the firm's objective. Kim et al. (2019) show that customer acquisition incentives induce the loan officers at a bank to engage in adverse customer selection; that is, salespeople leverage their private information to acquire lower quality customers who are easier to acquire. Such lower-quality loans default more and are long-run unprofitable to the firm. In the mobile hailing technology context, platforms provide the detailed pickup and drop-off information, and taxi drivers can select specific types of trips based on the private customer information. In the long run, this can hurt consumer welfare and make mobile hailing less attractive. The unintended consequences of information disclosure were discussed by Acquisti et al. (2016). Edelman et al. (2017) show that applicants' disclosed personal information, such as their names, is used against their applications in the Airbnb online rental market. Taxi drivers have long been accused of rejecting small-fare trips or trips to certain destinations. It is unclear whether the prevalence of the new mobile hailing technology could erase some of the gains in making taxi service more accessible to riders.

Earlier research on the taxi industry largely focused on the labor-supply decisions. The taxi industry offers a classical context to study labor supply. Camerer et al. (1997) and Farber (2008) used New York City taxi data and studied a daily income-targeting problem—whether drivers set a daily income target and work till the target is met. Frechette et al. (2019) also used New York City taxi data and estimated a dynamic daily entry and exit (stopping) decision model. Recent technology innovation can bring in permanent wage increases, which could possibly result in a higher shadow value of time and lead to fewer working hours (Farber 2015). Chen et al. (2017) document the value of ride-sharing platforms like Uber and Lyft in creating flexible work. They focus on a segment of people who are not professional taxi drivers but participate in the platforms to provide service on a flexible schedule. We instead focus on existing taxi drivers and investigate the changes in working hours before and after adopting mobile hailing apps. More importantly, labor supply is just one dimension of behavior changes. We investigate the impacts on multiple driving behaviors.

Taxi drivers decide not only on their working hours, but also which areas to cruise in their search for passengers. Buchholz (2015) studies taxi drivers' search strategies. He builds a dynamic spatial search equilibrium model of taxi supply and demand in each geographical point in each period across the day to recover search friction cost. In concluding, he conducts a counterfactual analysis to assume zero search friction for every simultaneously operating taxi to approximate an Uber-like market scenario. Zhang et al. (2018) also use taxi GPS data to model individual drivers' learning and search behaviors. They find, via a set of counterfactual analyses, that efficient information sharing leads to an income increase among all taxi drivers. The challenge is that even with the support of mobile hailing technology, one cannot infer zero search cost and perfect matching between riders and drivers. We do not impose this assumption.

In summary, we examine a setting where mobile hailing technology was introduced. We systematically evaluate driving behavior changes in multiple dimensions. Our goal is to understand whether there is a gain in hourly earnings after the adoption of mobile hailing technology and in which ways the gain occurs—whether taxi drivers' hourly earnings increase is via cruising-time reduction or trip selection in favor of longer trips.

3. Data

3.1. Market Background

Beijing has approximately 100,000 registered taxi drivers and 66,000 taxicabs, where the taxi licenses and fares are highly regulated by the local government.[1] The number of taxicabs has remained almost constant over the last 20 years, whereas the population has nearly doubled, leading to a shortage of taxi supplies (Geng and Mozur 2013). Approximately 70 million taxi trips occur each year.

The majority of the cabs are owned by cab companies (fleets). The standard employment arrangement of cab drivers involves a driver signing a single-shift or day-shift (night-shift) lease on a cab for a fixed period. A single-shift driver rents the cab for all the 24 hours in a day, whereas a day-shift driver has to share the cab with a night-shift driver. Each of the two drives the car for 12 hours, including either the morning rush hour at 7:00–9:00 a.m. or the evening rush hour at 5:00–7:00 p.m. A driver pays a monthly fixed rental fee for the cab plus the cost of fuel, and he keeps 100% of the fare income. The fixed fee varies from CNY 5,200 for a single-shift driver to CNY 4,100 for a day-shift (night-shift) driver.[2]

We explore the introduction of mobile hailing technology in the taxi industry in Beijing, China. The mobile hailing services were introduced around January 2013 by a few start-ups such as Didi and Kuaidi.[3] The mobile hailing apps started out providing services only to licensed cabs and later expanded into the private car business. Only registered taxi drivers were allowed to adopt the mobile apps in the period of our observation window. A driver needs to follow two steps to use an app. First, he needs to be equipped with a personal smartphone with an internet connection. Second, he needs to download the mobile hailing application to the smartphone and register an account using his cell phone number, driving license, photo ID, and bank account number. After completing these two steps, the driver is able to look for riders via the mobile hailing app. A driver receives notifications on the mobile app of the pickup and drop-off locations of requested rides.[4] He then decides to take a request or not. When the driver completes a trip, the fare is collected by the app from the rider's account and credited to the driver's bank account. No commissions are charged for the mobile rides by the apps.

There are a few unique features in this setting that facilitate exploration of the impact of mobile hailing technology. First, mobile hailing technology limited access to the taxi drivers already licensed by the city. Entry of new private drivers was restricted, such that the supply of taxi drivers was stable. Second, surge pricing was yet to be implemented by the local mobile hailing platforms, and Uber was yet to become available in Beijing during our observation window. Uber was introduced in Beijing in January 2015. This allows us to attribute driving behavior changes to the adoption of mobile hailing technology rather than a potential supply increase or the surge-pricing mechanism.

Taxi drivers earn income from trip fares. Similar to the two-part tariff in the United States, the taxi fares in Beijing consist of a one-time fixed fee and a distance-based fee. The details of the fare structure are reported in Table 1. Prior to June 2013, income was earned at the rate of CNY 10 for the first 3 kilometers and CNY 2 per kilometer up to 15 kilometers. When the customer travels beyond 15 kilometers, the rate increases to CNY 3 per kilometer. A significant fare change was implemented in June 2013, when the price was set at the rate of CNY 13 for the first 3 kilometers plus CNY 2.3 per kilometer up to 15 kilometers and CNY 3.5 per kilometer above 15 kilometers. Throughout the whole period, there was a night surcharge of CNY 2.4–4.2 per kilometer between 11:00 p.m. and 5:00 a.m., a waiting-time surcharge of CNY 2–2.3 every five minutes, a weekday peak-hour waiting-time surcharge of CNY 4–4.6 every five minutes, and a gas-tax surcharge. The key factors in a trip fare are travel distance, duration, and speed.

3.2. Driving Behavior Measures

The foundation of our empirical work is a 3.6-terabyte minute-by-minute geolocation data set of 2,106 randomly sampled single-shift drivers in Beijing. GPS trajectories were tracked over an 18-month period from January 2013 to June 2014. The data include information on each driver's GPS coordinates, driving direction, driving speed, and in-service state at each minute interval. The shift between cruising and in-service marks the beginning or the end of a trip, whereas the trip trajectory and pickup and drop-off locations can be inferred from the GPS coordinates. We calculate the fare and gas cost of each trip based on the price scheme and daily gas prices. We measure a trip's earnings as the difference between the trip fares and gas cost.

Taxi drivers' hourly earnings are the fares earned divided by the sum of the time spent driving passengers and cruising in search of new passengers. Trip fares are mostly determined by driving distance and highly correlated with driving time. The key factor in determining hourly earnings is the relative ratio between driving and cruising time. Mobile hailing technology that reveals the detailed pickup and drop-off locations offers two distinct approaches to increasing a taxi driver's hourly earnings. Taxi drivers can reduce the cruising time between trips with the help of the mobile hailing technology. Alternatively, they can increase hourly earnings by engaging in trip selection in favor of longer trips. Given the same cruising time, a longer trip brings in more earnings, increases the relative ratio of driving over cruising time, and boosts the hourly earnings.

To account for the heterogeneous effects across different geographic areas, we need to classify different regions in the city and standardize the driving behaviors in each region. The spatial partition of Beijing is not intuitive. The city's layout does not resemble a Manhattan street system that is laid mostly out on a uniform grid of streets and avenues. We need

Table 1. Taxi Fare Structure in CNY

	Before June 10, 2013	After June 10, 2013
Base fee for the first 3 km	10.0	13.0
Per additional kilometer (3–15 km)	2.0	2.3
Per additional kilometer (≥15 km)	3.0	3.5
Night hour per additional kilometer (3–15 km)	2.4	2.8
Night hour per additional kilometer (≥15 km)	3.6	4.2
Waiting time per five minutes	2.0	2.3
Waiting time per five minutes (rush hour)	4.0	4.6
Gas tax	0.0	1.0
Gas tax after 3 km	3.0	0.0

Notes. Numbers are in Chinese yuan (CNY). In January 2013, CNY 1 equaled USD 0.16.

a city partition that takes into account traffic density and points of interest on streets, intersections, and even alleyways. An advantage of our data is that the observed frequencies of pickup and drop-off GPS coordinates are a good measure of traffic density. We extracted the first week's pickup and drop-off coordinates from the taxi trajectory data (week 1 in 2013). Repetitive records of location coordinates are kept to indicate traffic density. We apply a hierarchical density-based clustering method, namely, hierarchical density-based spatial clustering with application with noise (HDBSCAN; Campello et al. 2013),[5] to classify all these GPS coordinates to 97 areas so that the traffic density is relatively similar within each cluster that can be treated as one area.

Figure 1 provides an overview of the partitioning of Beijing. Each dot indicates a pickup or drop-off point. When connected, the dots depict well the roads, building blocks, and street intersections. For example, the blank area in the center of the map is the Forbidden City. The highlighted circle zooms in on a five-mile (eight-kilometer) area around the Forbidden City. Our map shows that most of the area boundaries are at road intersections and that the areas are not restricted to a certain shape (e.g., rectangular).

We also accommodate the temporal–spatial perspective in the measures of trip distance and cruising time. We give each trip an area and time tag using the trip pickup location and the starting time. We measure the cruising time as the duration between the end of the last trip and the start of a new trip. We use the Herfindahl index to measure cruising area concentration. At each drop-off location, a driver faces a route choice that connects the drop-off area with all the neighboring areas (based on city partition in the last section). We calculate the route-choice percentages of all the neighboring areas every time a driver delivers a passenger. The larger the index, the more concentrated a driver's search direction.

Figure 1. Five-Mile Zoom-In of the City Partition Using Drivers' Drop-Off and Pickup Data

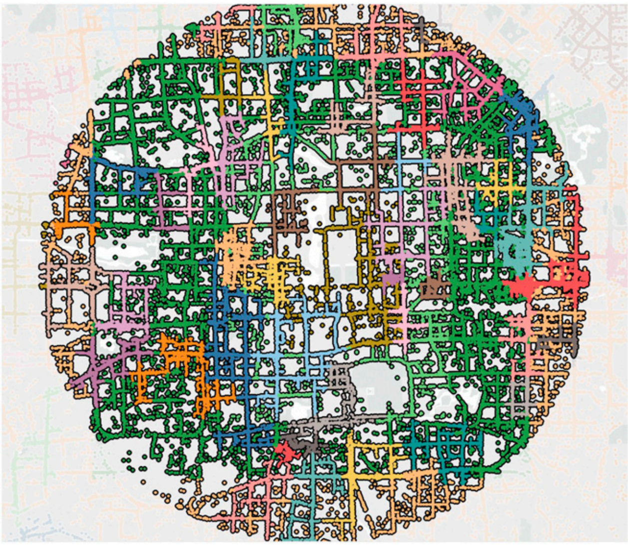


Table 2 provides a summary of all the driving behavior measures along with hourly earnings. The average hourly earnings is CNY 36. An average single-shift driver works for approximately 10 hours a day and delivers 17.5 rides. Cruising time varies considerably at different times of a day across different locations. We consider 7:00–9:00 a.m. and 5:00–7:00 p.m. to be rush-hour periods and the rest to be nonrush hours based on the fare structure. We further cluster the 97 areas into two spatial zones, a high-traffic zone and a low-traffic zone, by the number of trips initialized from that area in the first month. The two-by-two temporal–spatial framework approximates different levels of local demand. As can be seen from Table 2, it takes less than 10 minutes to search for a trip during rush hours, whereas drivers, on average, spend more than 10 minutes to find a trip during nonrush time periods. We do not find a significant difference in the trip distance by time period or location. The Herfindahl concentration measure is very close to zero. It suggests that drivers, on average, cruise across all possible neighborhoods rather than stick with a certain area.

3.3. Model-Free Evidence

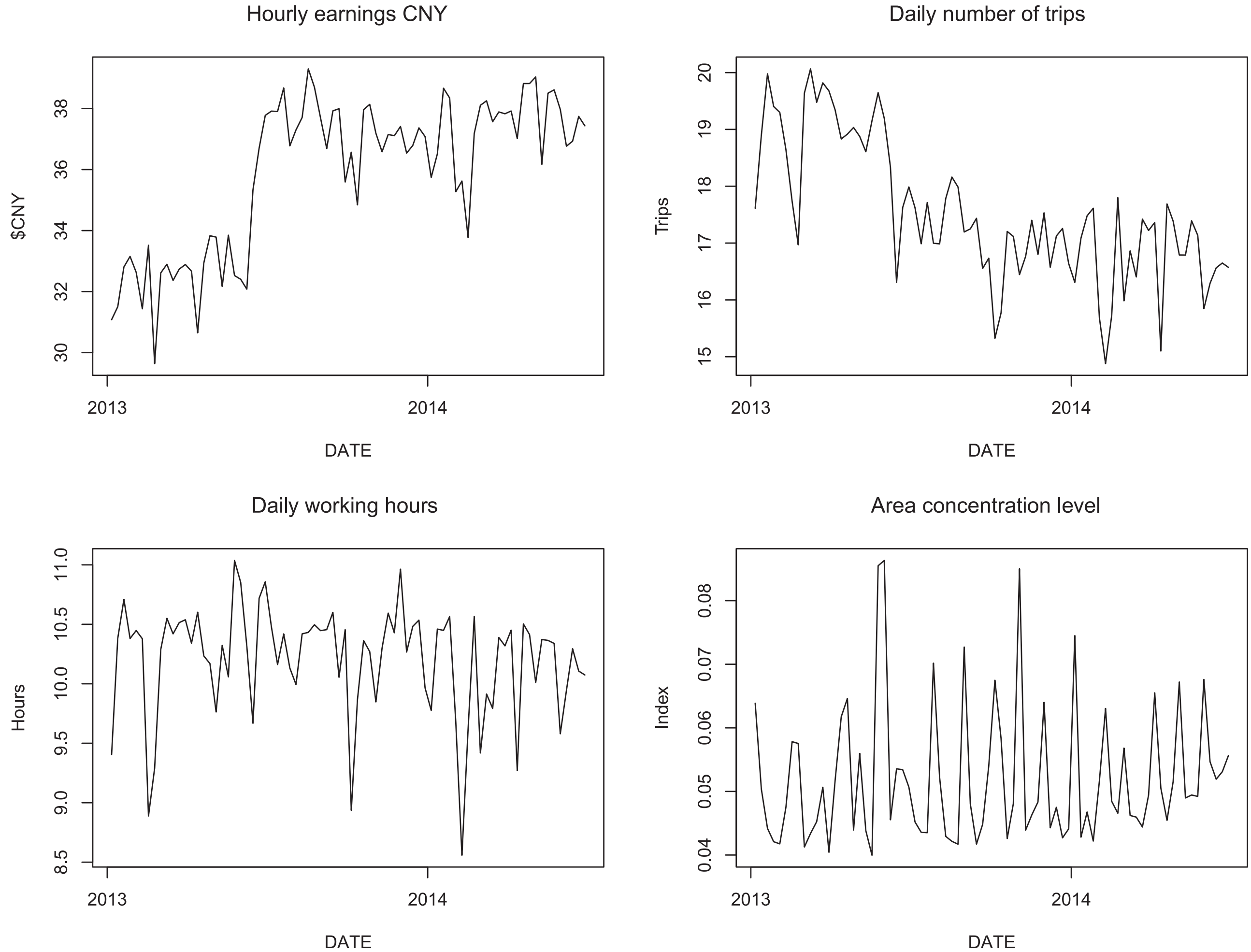
We now present several forms of model-free evidence on the driving behavior changes over the 18 months after the introduction of mobile hailing technology. Figure 2 shows that the average hourly earnings increased from CNY 32 to CNY 38. Drivers reduced their daily working hours by approximately 20 minutes over time and cut their daily trips from 19 to 17 per day. The Herfindahl concentration index slightly

Table 2. Summary Statistics of the Data Sample

	Mean	S.D.	Q1	Q3
Hourly earnings	35.89	7.82	30.92	41.14
Daily working hours	10.20	2.82	8.30	11.85
Daily number of trips	17.52	6.47	13.00	21.33
Cruising time between trips (minutes)				
Rush hour, high-traffic area	9.83	13.63	2.12	12.03
Non–rush hour, high-traffic area	10.22	15.22	2.33	12.28
Rush hour, low-traffic area	9.47	14.84	2.02	11.02
Non–rush hour, low-traffic area	10.35	16.54	2.12	12.03
Trip distance (kilometers)				
Rush hour, high-traffic area	7.61	7.12	2.80	10.05
Non–rush hour, high-traffic area	7.81	7.42	2.73	10.41
Rush hour, low-traffic area	7.19	7.00	2.63	9.25
Non–rush hour, low-traffic area	7.68	7.62	2.62	9.98
Concentration index	0.05	0.03	0.04	0.06

Notes. Summary statistics are based on 2,106 single shift taxis with the complete minute-level GPS information across the sample period. S.D., standard deviation; Q, quartile.

Figure 2. Trends of Hourly Earnings, Number of Trips, Working Hours, and Concentration Level



increased over time, suggesting that drivers tended to choose cruising areas less randomly.

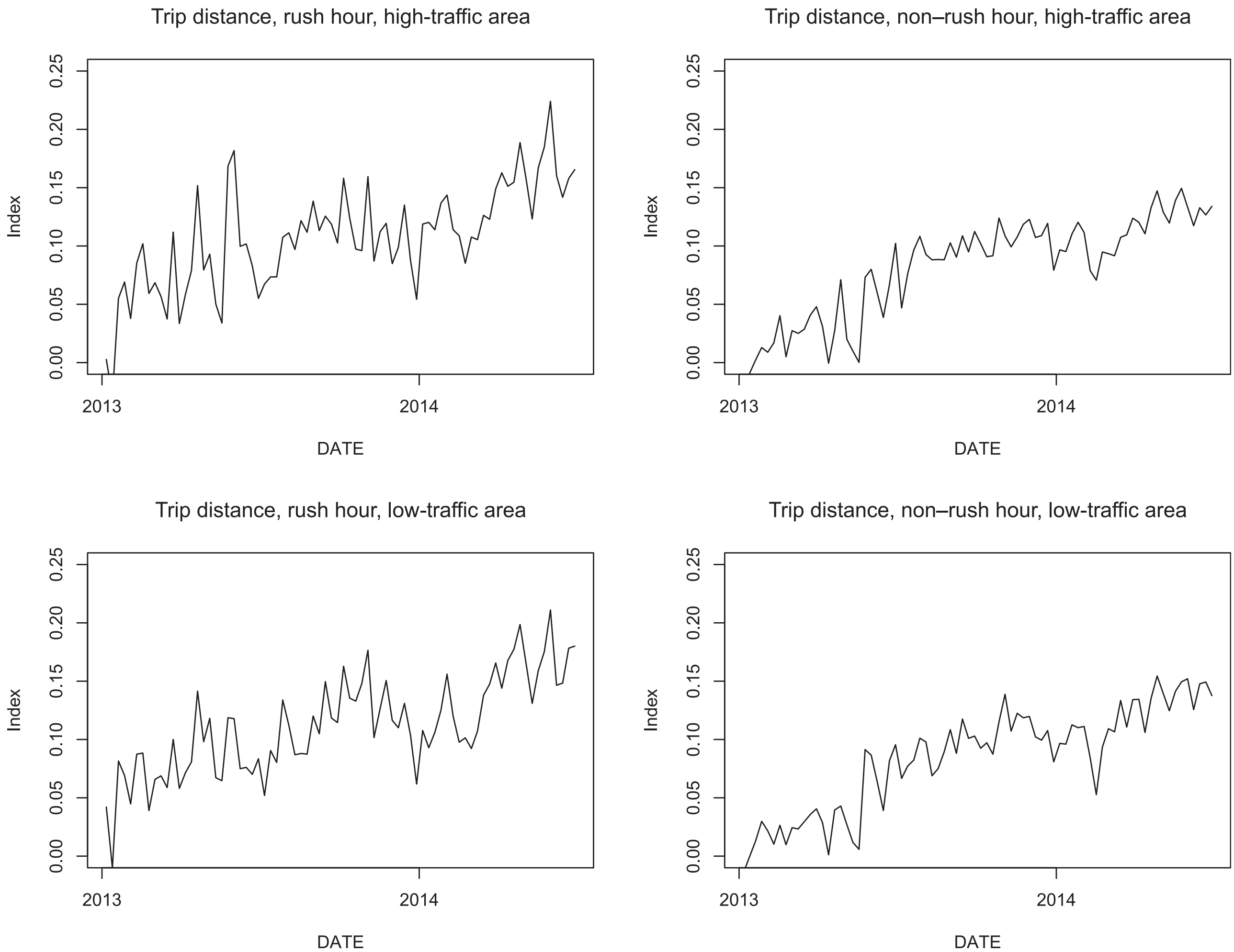
Trip distance is highly dependent on the pickup locations, as central and suburban areas can have very different building densities. To directly compare the changes in trip distance across areas over time, we consider the combination of a city area and a 15-minute interval as a market. We normalize the trip distance by the first-two-week average in each market. For example, if the average trip distance originating from area 22 at 8:00 p.m. is 10 kilometers with a standard deviation of 1.5 kilometers, then a 11.5 kilometer trip originating from the same market in week 8 will have a normalized index of $(11.5 - 11)/1.5 = 1.0$. Figure 3 shows the trends in the normalized trip distance for each of the two-by-two temporal–spatial combinations. Interestingly, there is a steady increase in trip distance across all the temporal and spatial combinations. The increase is larger during rush hours compared with nonrush time periods. There is a minimal difference in the trends between high- and low-demand areas. We construct the normalized cruising time index in the same way. Figure 4 shows that cruising time slightly increased around the time of fare adjustment in June 2013 and remained about the same over time. The pattern holds in each of the time and location combinations.

The model-free evidence is important for our subsequent model development. The data show that the prevalence of mobile hailing technology is associated with an increase in hourly earnings, a drop in the number of daily trips, and a drop in working hours. When it comes to the mechanism, the evidence seems to be in favor of trip selection rather than idle-time reduction. It highlights the importance of evaluating the impact of adoption across all the driving behaviors rather than just one or a few dimensions.

4. Model

In this section, we develop our model to evaluate the impact of mobile hailing technology on multiple dimensions of driving behaviors. A challenge

Figure 3. Trends of Trip Distance by Time Periods and Traffic Areas

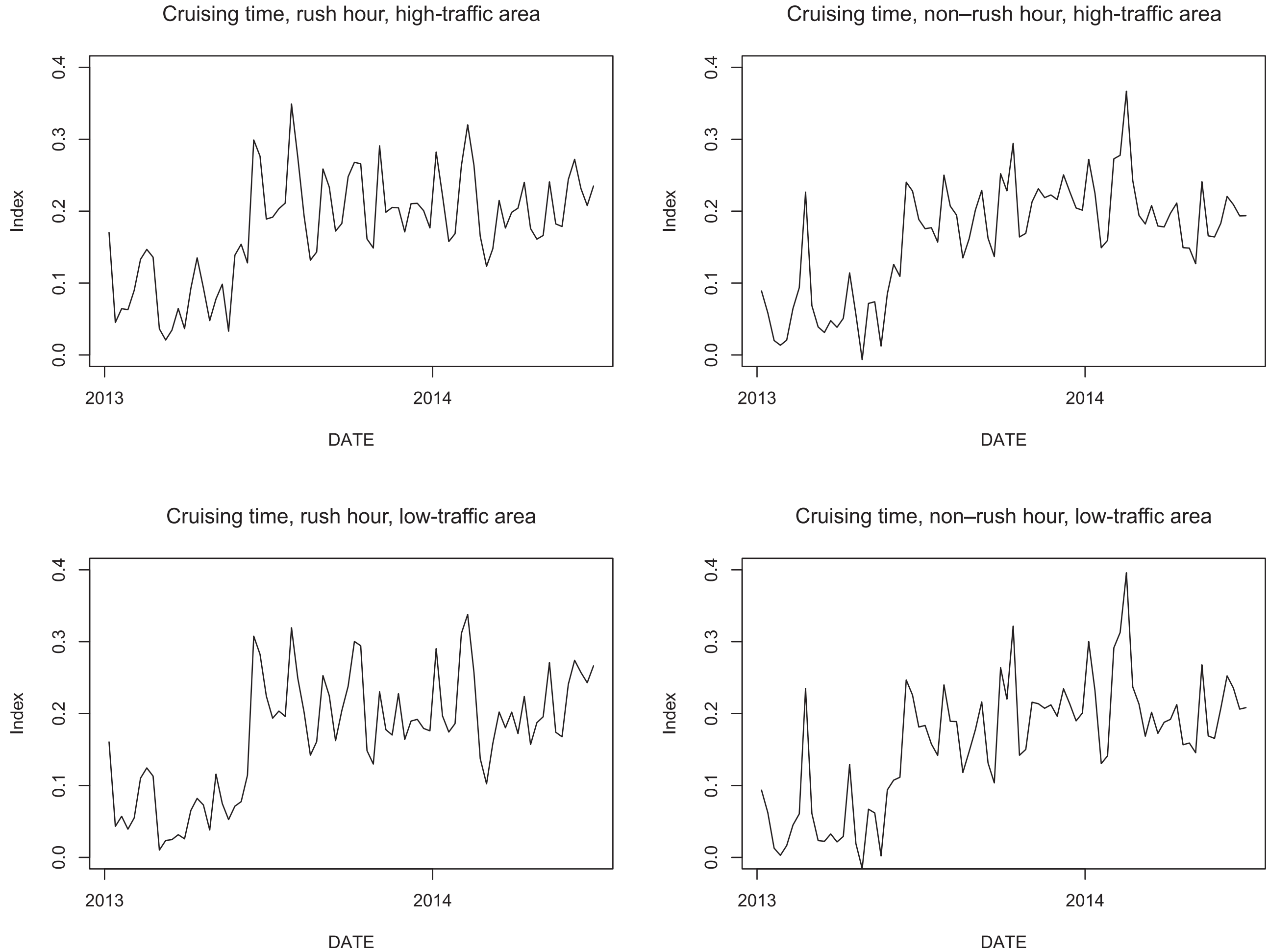


in the data is that we do not observe individual driver's adoption timing of mobile hailing technology. To overcome this challenge, we build a modified change-point model that detects the unobserved adoption decision via observed systematic changes in driving behaviors. Our change-point model falls in a general class of state-space models. These models are centered on an enduring but nonstationary stochastic process that assumes the observation units change their parameters at random points over time. The objective is to infer the locations of the change points along with the values of changes (Barry and Hartigan 1993, Chib 1998). In the marketing literature, change-point models have been applied to capture the underlying evolution of trial-repeat processes for new products under the assumption that the preference parameters in the two stages are behaviorally distinct (Fader et al. 2004, Schweidel and Fader 2009). Another specific subclass of state-spaces models is the hidden Markov model (MacDonald and Zucchini 1997), which allows transitions across finite but unobserved segment states over discrete time periods (Montgomery et al. 2004, Netzer et al. 2008, Fader et al. 2010, Park and Gupta 2011, Ma et al. 2015). For example, Netzer et al. (2008) defined three unobserved relationship states that varied by relationship strength and inferred each customer's posterior probability of being in each of the states from his or her observed gift-giving behaviors. We adopt the framework of a traditional change-point model. We attempt to infer drivers' app-adoption decisions and the parameter changes related to their driving behaviors. Our model can also be considered as a two-state hidden Markov model with one state as technology adoption and the other state as no adoption.

4.1. Impacts of Mobile Hailing Technology

We use W to denote the 11 measures of the five components of driving behaviors, including the daily number of trips (ln), daily working hours (ln), cruising time in the rush versus nonrush periods and high- versus low-traffic areas, trip distance in the rush versus nonrush periods and high- versus low-traffic areas, and cruising area concentration index (ln). The unit of

Figure 4. Trends of Cruising Time by Time Periods and Traffic Areas



analysis is at the driver-week level, where W_{ikt} denotes taxi driver i's driving behavior k in week t. We model driving behavior W_{ikt} as

$$W_{ikt} = \alpha_{k,s_{it}} + \beta_{k,s_{it}} E_i + \tau_{k,s_{it}} R_t + X_t \lambda_k + \xi^W_{kt} + \zeta^W_{ik} + \varepsilon_{ikt}. \tag{1}$$

Here, s_{it} denotes driver i's adoption state in week t; $s_{it} = 1$ indicates driver i uses mobile hailing technology in week t, and $s_{it} = 0$ indicates no adoption yet by week t. All the parameters in Equation (1) may vary depending on the underlying adoption state s_{it}. We set $s_{i0} = 0$ for all drivers at the introduction of mobile hailing technology in January 2013. We provide more details on the evolution of adoption state s_{it} in the next subsection.

Let us take the daily number of trips ($k = 1$) as an example for Equation (1). We specify that the daily number of trips $W_{it,k=1}$ is driven by four factors. The first is a baseline daily number of trips α_k. Second, we allow the baseline to vary by individual driving skill E_i. We construct the measure of driving skill E_i using the driver's earnings in the initialization period (January 2013). We normalize E_i to have a mean of 0 and a standard deviation of 1, such that the interpretation of baseline α_k is more straightforward. Specifically, baseline α_k refers to the daily number of trips of an average skilled taxi driver. Third, we include the market adoption rate of mobile hailing technology to indicate the changing competition environment. As the adoption rate grows, drivers who do not adopt may face increasing competition from those who adopted. We also include control variables, including a new fare change dummy, Chinese New Year observations, National Day observations, and the numbers of days in a week that are above 30°C, below 5°C, rainy, snowy, foggy, and smoggy, respectively. During the Chinese New Year and the National Day period, taxi supply drops significantly. Driving behavior also varies by the weather conditions. For example, snow or fog would slow down the driving speed. Last, we decompose the error terms into ξ^W_{kt}, ζ^W_{ik}, and ε_{ikt}. Term ξ^W_{kt} captures unobserved time-varying market shocks beyond what is captured in the observed control variables X_t. We allow the shocks to be specific to each driving behavior k. Term ζ^W_{ik} indicates the random effect that captures unobserved individual heterogeneity in the baseline driving behavior beyond the observed driving skill E_i. Terms ε_{ikt} are the random errors that collectively follow the multivariate normal distribution as $\varepsilon_{it} \sim N(0, \Sigma_\varepsilon)$.

We can rewrite Equation (1) to account for interactions between adoption state s_{it} and the parameters. The specification allows us to answer whether the adoption of mobile hailing technology changes the response parameters of α_k, β_k, and τ_k:

$$W_{ikt} = (\alpha_k + \Delta\alpha_k s_{it}) + (\beta_k + \Delta\beta_k s_{it})E_i + (\tau_k + \Delta\tau_k s_{it})R_t + X_t\lambda_k + \xi_{kt}^W + \zeta_{ik}^W + \varepsilon_{ikt}. \quad (2)$$

Equation (2) speaks directly to a variety of possible impacts of mobile hailing technology. Term $\Delta\alpha_k$ focuses on the shift of baseline driving behavior k. When driver i adopts mobile hailing technology ($s_{it} = 1$), there can be $\Delta\alpha_k$ change in his baseline driving performance α_k. The sign and magnitude of $\Delta\alpha_k$ show whether and the extent to which mobile hailing technology has an immediate impact on driving behavior k.

The adoption of mobile hailing technology may render the human driving skill E_i more or less important. The term $\Delta\beta_k$ captures the change in the importance of driving skill. A consistent sign between β_k and $\Delta\beta_k$ indicates that human driving skill becomes even more important after the new technology adoption, which is a synergistic effect. An opposite sign between β_k and $\Delta\beta_k$ indicates that the new mobile hailing technology works as a substitute for human capital, reducing the importance of individual driving skill.

We allow for the interaction between individual adoption state s_{it} and market adoption rate R_t, as drivers may be subject to different market competition depending on their adoption state ($s_{it} = 1$ versus $s_{it} = 0$). A negative τ_k suggests that a driver's performance in dimension k will decrease as the market adoption rate of mobile hailing technology increases. If this is coupled with $\Delta\tau_k > 0$, it suggests that the diminish is less for those who adopt the apps than those who do not. For example, a driver's cruising time may increase as more drivers adopt the apps. Those who do not adopt the apps could suffer from the prevalence of the mobile hailing technology. A digital divide could be created between the adopters and the nonadopters.

It is important to note that we do not impose a pattern of driving behavior changes. The only assumption we make is that the adoption of mobile hailing technology will induce a change in at least 1 of the 11 measures of driving behaviors. However, we do not restrict where the changes may occur. They may occur in cruising time, trip distance, working hours, or even all the driving behaviors. To put it another way, we do not assume that the adoption of mobile hailing technology will bring about changes in all the response parameters α_k, β_k, and τ_k across all the 11 driving behaviors. There can be a very flexible combination of $\Delta\alpha_k$, $\Delta\beta_k$, and $\Delta\tau_k$.

4.2. Evolution of Mobile Hailing Technology Adoption

Now we look at the evolution of adoption state s_{it} over time. If the taxi driver adopts mobile hailing technology at week $t-1$, we assume that he continues using the mobile applications for the rest of the observation period. Thus, we have

$$[s_{it} | s_{i,t-1} = 1] = 1. \quad (3)$$

If the driver has not adopted mobile hailing technology at week $t-1$ yet ($s_{i,t-1} = 0$), he may adopt the technology with the following rule:

$$[s_{it} | s_{i,t-1} = 0] = \begin{cases} 1 & \text{if } u_{it} \geq 0, \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

Here, u_{it} is the underlying adoption utility with the following specification:

$$u_{it} = \gamma_0 + \gamma_1 E_i + \gamma_2 R_{t-1}(1 - R_{t-1}) + \gamma_3 Neighbor\ R_{it-1} + \gamma_4 Peer\ R_{it-1} + \zeta_i^A + \epsilon_{it}, \quad (5)$$

where γ_0 is a baseline adoption propensity common across all the individuals. We include driving skill E_i to test whether drivers with different skills may systematically differ in their adoption probabilities of mobile hailing technology. We also accommodate the technology diffusion process via $R_{t-1}(1 - R_{t-1})$ as in the Bass (1969) diffusion model. The term ζ_i^A is added in the adoption probability to represent unobserved individual heterogeneity in the adoption tendency, and ϵ_{it} is a random error following a standard normal distribution. Given this formulation, the conditional adoption probability follows a probit model.

A selection issue may arise if there are correlations between the individual unobservables ζ_i^A in the adoption decision Equation (5) and the individual unobservables ζ_{ik}^W in the driving behavior Equation (2). For instance, a driver who chooses to adopt the mobile hailing application may expect a higher return on adoption. Additionally, unobserved individual characteristics may affect both the adoption decision and the postadoption driving behaviors. The impact of mobile hailing technology adoption could be overestimated without a control for the selection bias. We let the unobserved individual heterogeneity in the adoption and driving behavior equations, $\zeta_i = (\zeta_{ik}^W, \zeta_i^A)$, have a joint normal distribution with means zero and a full variance–covariance matrix, $\zeta_i \sim N(0, \Sigma_\zeta)$. Our approach is similar in spirit to that of Gopalakrishnan et al. (2017), who allow for the correlation between the unobserved change-point state and the observed behavioral patterns, and adopt a Bayesian framework to allow the change point to be flexible/different for each individual but still pool with the relevant peers via the prior.

If we do not find significant off-diagonal correlations, it suggests that the unobserved market forces that drive the market adoption rate and the driving behaviors follow two separate processes. This would provide evidence against the self-selection concern. We also need exclusion variables that can shift the adoption tendency but do not affect driving behaviors. Such exclusion variables need to vary across drivers and time periods. We created two exclusion variables. One is the last week's number of adopters (ln) among local neighbors within a two-kilometer radius, *Neighbor* R_{it-1}. We rationalize that the neighbors' usage of mobile hailing technology will affect the target driver's adoption propensity via word of mouth. A large population of taxi drivers in Beijing live in a few taxi driver communities. We infer drivers' home addresses from the GPS locations where they regularly start and end their daily jobs. A limitation of this exclusion variable is that local neighbors' driving behaviors may also be correlated because of social influence or common preference, although we show empirically that the driving behaviors among local neighbors are at most weakly correlated.[6] To overcome this limitation, we take leverage of the random encounters with unknown peer drivers on the road. We use the last week's number of adopters (ln) among all the randomly encountered peer drivers, *Peer* R_{it-1}, as a second exclusion variable. We consider two taxi drivers remaining in the same location (within a 100-meter radius) for more than 10 minutes as a random encounter. This mostly occurs when taxi drivers dine at the same restaurant or wait at a gas station. Given the nature of taxi driving, whom the focal driver encounters and when should be random. We speculate that these encounters may involve conversations on mobile hailing technology. Thus, the number of adopters (ln) among the randomly encountered peer drivers last week would affect the focal driver's adoption decision.

There is another separate concern of endogeneity between market adoption rate R_t and market shocks ξ_{kt} in the driving behavior Equation (2). We look for instruments that shift market adoption rate in the current period but do not affect the same period's driving behaviors. We use the last period's adoption rate, R_{t-1}, and the last period's search index of smartphones on Baidu, $SearchSmartPhone_{t-1}$, as two instruments. The choice of last period's adoption rate is intuitive. We choose the smartphone search index as an alternative instrument because a smartphone is a necessity to install mobile apps, but smartphone ownership should not be related to driving behaviors. We write the current-period adoption rate as a function of the two instruments:

$$R_t = \delta_0 + \delta_1 R_{t-1} + \delta_2 SearchSmartPhone_{t-1} + \xi_t^R. \quad (6)$$

In addition, we allow for an unrestricted variance–covariance matrix between market shock ξ_{kt}^W in the driving behavior and the shock ξ_t^R in the adoption rate, $\xi_t = (\xi_{kt}^W, \xi_t^R) \sim N(0, \Sigma_\xi)$. Any nonzero off-diagonal element in the variance–covariance matrix is evidence of endogeneity. It suggests that market shocks unobserved to us researchers could affect the market adoption rate as well as driving behaviors.

5. Estimation

5.1. Estimation Steps

We propose a Bayesian Markov chain Monte Carlo algorithm with data augmentation to reduce the computational burden of estimating the full likelihood function. Data augmentation is necessary in our setting because we need to integrate over the adoption state variable s_{it} in computing the full likelihood. This cannot be efficiently achieved using classic approaches. Given that there is at most one change point, the state variable is fully determined by the specific time period each driver adopts the mobile hailing technology. We use a_i to indicate the adoption period $(1, 2, \ldots, t)$ and augment this variable in the estimation process. Our algorithm also combines individual-level panel data with aggregate-level survey information.

There are four sets of parameters we estimate: (1) parameters that govern the adoption probability, $\gamma = \{\gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4\}$; (2) adoption-state-specific parameters in the driving behavior equation, $\Theta = \{\alpha, \beta, \tau\}$ and $\Delta\Theta = \{\Delta\alpha, \Delta\beta, \Delta\tau\}$; (3) parameters of instrumental variables in the endogenous adoption equation, $\delta = \{\delta_0, \delta_1, \delta_2\}$; and (4) the variance–covariance matrices, Σ_ε of the error terms in the behavior equation, Σ_ζ of unobserved individual heterogeneity that relate to self-selection, and Σ_ξ of market shocks that relate to endogeneity.

We denote the likelihood of observing each individual's driving behavior across the data periods as $L_i(W_i)$. We denote the user- and adoption-specific attributes as $H_{it} = [1, E_i, R_t]$. Conditional on the augmented adoption period a_i, individual-specific random effect ζ_i, and period-specific market shocks ξ_t, the likelihood can be formulated as

$$\begin{aligned} &L_i(W_i \mid a_i, \zeta_i, \{\xi_t\}, \Theta, \Delta\Theta, \lambda, \Sigma_\varepsilon) \\ &\quad = \prod_{t=1}^{a_i-1} \Phi(\mathrm{e}_{it|s_{it}=0}, \mathbf{0}, \Sigma_\varepsilon) \prod_{t=a_i}^{T} \Phi(\mathrm{e}_{it|s_{it}=1}, \mathbf{0}, \Sigma_\varepsilon), \end{aligned} \quad (7)$$

where $\mathrm{e}_{it|s_{it}=0} = W_{it} - H_{it}\Theta - X_t\lambda - \zeta_i^W - \xi_t^W$ and $\mathrm{e}_{it|s_{it}=1} = W_{it} - H_{it}(\Theta + \Delta\Theta) - X_t\lambda - \zeta_i^W - \xi_t^W$, and $\Phi(\cdot)$ is the probability density function of a multivariate normal distribution. We proceed with eight iterative steps in our MCMC estimation (see details in Web Appendix A).

5.2. Survey Data Augmentation

Change-point models typically rely on the systematic shifts in the observed variables to infer the switching between underlying states (Montgomery et al. 2004, Netzer et al. 2008, Fader et al. 2010, Park and Gupta 2011, Ma et al. 2015). To increase the validity of the change-point identification, we conducted a survey among 285 taxi drivers in various areas of Beijing in 2015 and constructed a revealed adoption curve of mobile hailing technology over the same period of our observation window. We incorporate the revealed adoption survey data in our change-point model to help infer the adoption decisions in our data sample. Essentially, the survey respondents share the same adoption process as our panel taxi drivers, as both the samples are randomly drawn from the same population. When we evaluate the parameters γ in the adoption Equation (5), we consider not only how the parameters γ would infer the adoption decision a_{it} and the driving behaviors of the taxi driver panel, but also how the γ fits the observed adoption curve of the survey sample. Our approach is similar to those in previous research that augments the estimation of individual-level secondary data with aggregate-level survey information (Petrin 2002, Chintagunta and Dube 2005).

Let us denote the adoption period for each respondent j in the survey sample as a_j^S. We can write the posterior distribution of the adoption parameters γ as

$$\begin{aligned}\pi\left(\gamma \mid \{a_i\}, \{a_j^S\}, Z_{it}, \{\zeta_i^A\}\right) &\propto \prod_{i=1}^{N} L_i\left(a_i \mid Z_{it}, \gamma, \zeta_i^A\right) \\ &\times \prod_{j=1}^{J} L_j\left(a_j^S \mid \gamma, \{Z_{it}\}, \{\zeta_i^A\}\right) \times \pi(\gamma), \end{aligned} \tag{8}$$

where $Z_{it} = [1,\ E_i,\ R_{t-1}(1 - R_{t-1}),\ Neighbor\ R_{it-1},\ Peer\ R_{it-1}]$, and N and J are the numbers of drivers in the estimation and the survey samples, respectively.

Denote by $\phi(\cdot)$ the probability density function of the standard normal distribution. We can write out the adoption likelihood L_i of taxi driver panelists as

$$L_i\left(a_i \mid Z_{it}, \gamma, \zeta_i^A\right) = \phi\left(Z_{ia_i}\gamma + \zeta_i^A\right) \prod_{t=1}^{a_i-1}\left[1 - \phi\left(Z_{it}\gamma + \zeta_i^A\right)\right],$$

We can also write out the adoption likelihood L_j of surveyed drivers as

$$L_j\left(a_j^S \mid \{Z_{it}\}, \gamma, \{\zeta_i^A\}\right) = \frac{1}{N}\sum_{i=1}^{N} L_i\left(a_j^S \mid Z_{it}, \gamma, \zeta_i^A\right).$$

The likelihood of observing a_j^S from the survey depends on survey driver j's characteristics Z_{jt} and ζ_j^A. However, we do not observe it in the survey data. Instead, we observe the empirical distributions of Z and ζ from the taxi driver panel data. Therefore, we use numerical integration to make draws for Z and ζ from their empirical distributions and integrate them out in the likelihood function L_j of the survey data. This is how we leverage the survey information regarding the aggregate-level adoption rate over time.

5.3. Simulation

We conduct a few simulation studies to ensure that our estimation approach can recover the model parameters. We report the details of these simulations in Web Appendix B. In each of the simulation, we simulate the adoption decisions and the driving behaviors for 1,000 taxi drivers over 100 periods. We also simulate 100 surveyed taxi drivers. We show that we are able to recover the parameters in both the adoption decision equation and the driving behavior equation within a 95% confidence interval (CI). Our proposed modified change-point model is also able to recover the unobserved adoption decisions based on the observed driving behavior changes. We also carry out additional simulations with regards to the importance of the augmented survey information. We vary the survey sample size from 30 to 100. We show that the survey information is useful to the recovery of adoption decisions and that the results are not sensitive to the sampling error in the survey data as long as the survey sample size is relatively small compared with the taxi panel size.

6. Results

We run a total of 100,000 MCMC iterations and report the posterior distribution of the parameters based on the last 50,000 draws.

6.1. Impacts of Mobile Hailing Technology

We summarize the estimation results in Table 3. The baseline intercepts of the 11 driving behaviors are reported in column (1). The estimates of $\Delta\alpha$ in column (2) speak directly to the immediate impacts of adoption on driving behaviors when the apps were just launched on the market. We find that mobile hailing technology adoption significantly reduces working hours ($\Delta\alpha_1 = -0.046$). The number of trips is reduced but not statistically significant ($\Delta\alpha_2 = -0.031$). Immediately after adopting the mobile hailing applications, an average skilled taxi driver was able to reduce cruising time of trips at both rush and nonrush time periods in both high- and low-traffic areas, although the cruising-time reduction was more substantial in high-traffic areas than low-traffic areas ($\Delta\alpha_3 = -0.153$ versus $\Delta\alpha_5 = -0.065$). This is reasonable, as the information

Table 3. Model Estimation Results

	Baseline		Skills		Adoption rate R_t	
	(1)	(2)	(3)	(4)	(5)	(6)
	α	$\Delta\alpha$	β	$\Delta\beta$	τ	$\Delta\tau$
Working hours (ln)	**2.140**	**−0.046**	**0.186**	**−0.135**	−0.398	**0.249**
	(1.867, 2.432)	(−0.075, −0.007)	(0.180, 0.194)	(−0.140, −0.131)	(−0.405, 1.404)	(0.118, 0.342)
Number of trips (ln)	**2.900**	−0.031	**0.262**	**−0.289**	0.234	−0.023
	(2.615, 3.140)	(−0.068, 0.003)	(0.252, 0.272)	(−0.295, −0.282)	(−0.850, 1.553)	(−0.133, 0.074)
Cruise time index						
Rush hour, high-traffic area	0.057	**−0.153**	**−0.096**	**0.138**	0.062	**0.462**
	(−0.258, 0.395)	(−0.201, −0.092)	(−0.105, −0.081)	(0.127, 0.147)	(−1.821, 1.574)	(0.277, 0.599)
Non–rush hour, high-traffic area	0.075	**−0.126**	**−0.076**	**0.094**	0.095	**0.438**
	(−0.129, 0.305)	(−0.156, −0.080)	(−0.085, −0.066)	(0.088, 0.101)	(−0.780, 1.130)	(0.291, 0.540)
Rush hour, low-traffic area	0.070	**−0.065**	**−0.104**	**0.163**	−0.023	**0.238**
	(−0.269, 0.382)	(−0.113, −0.016)	(−0.116, −0.092)	(0.154, 0.174)	(−1.195, 1.487)	(0.010, 0.385)
Non–rush hour, low-traffic area	−0.025	**−0.091**	**−0.089**	**0.116**	−0.010	**0.332**
	(−0.371, 0.450)	(−0.141, −0.051)	(−0.099, −0.079)	(0.108, 0.123)	(−1.554, 1.231)	(0.195, 0.485)
Trip distance index						
Rush hour, high-traffic area	0.044	**0.048**	**−0.021**	**0.167**	0.231	**0.398**
	(−0.340, 0.335)	(0.001, 0.098)	(−0.033, −0.011)	(0.158, 0.176)	(−1.448, 1.744)	(0.252, 0.542)
Non–rush hour, high-traffic area	0.038	**0.072**	**−0.013**	**0.156**	0.087	**0.354**
	(−0.197, 0.317)	(0.048, 0.097)	(−0.024, −0.003)	(0.150, 0.162)	(−1.206, 1.350)	(0.277, 0.435)
Rush hour, low-traffic area	0.005	0.037	**−0.034**	**0.195**	0.223	**0.510**
	(−0.405, 0.388)	(−0.015, 0.090)	(−0.047, −0.020)	(0.184, 0.206)	(−1.459, 2.086)	(0.357, 0.640)
Non–rush hour, low-traffic area	−0.022	**0.067**	**−0.022**	**0.174**	0.199	**0.380**
	(−0.240, 0.276)	(0.038, 0.100)	(−0.033, −0.011)	(0.167, 0.182)	(−0.835, 1.332)	(0.289, 0.475)
Cruising area concentration index (ln)	**−2.835**	**0.261**	**−0.195**	**0.176**	−0.266	**−0.918**
	(−3.181, −2.528)	(0.232, 0.299)	(−0.207, −0.184)	(0.169, 0.183)	(−1.718, 1.276)	(−1.017, −0.841)
Log-likelihood	−651,872					
Number of observations	164,268					

Notes. Numbers in parentheses represents the 95% credible intervals. The bold indicates that the 95% credible interval does not contain zero. We also include control variables in each driving performance equation. The control variables include the new fare change dummy, Chinese New Year observations, National Day observations, and the numbers of days that are above 30°C, below 5°C, rainy, snowy, foggy, and smoggy, respectively, within a week.

role of mobile hailing technology would be limited in low-traffic areas. Even in the ideal case that a taxi driver is notified of a nearby waiting passenger immediately when he completes his last trip, he may not be able to substantially reduce cruising time if the nearest trip by pickup request is still kilometers away. When it comes to trip distance, we find that the revealed drop-off and pickup locations facilitate trip selection in favor of long trips. The average trip distance significantly increases in three out of the four temporal–spatial combinations (e.g., $\Delta\alpha_7 = 0.048$). We do not find a significant difference in the increase in trip distances between rush and nonrush time periods or between low- and high-demand areas. Finally, app adoption changes a driver's search directions. We find that there is a significantly higher level of cruising route concentration as drivers are attracted to areas with mobile ride requests ($\Delta\alpha_{11} = 0.261$). Overall, in the beginning, when the apps were just launched, the adopting taxi drivers took the same number of trips but worked significantly fewer hours. Given the revealed local demand, they were able to spend less time searching for trips. They were also able to select longer and larger-fare trips. The increase in the relative ratio of driving and cruising time and the increase in trip fares together improved the app-using driver's hourly earnings at the early stage of the app launch.

The estimates in column (3) speak to whether the baseline driving behaviors differ across drivers with various skills. It shows that individual driving skills capture the variations in driving behaviors. Highly skilled drivers (i.e., $E_i = 1$) make significantly more trips ($\beta_2 = 0.262$) and work significantly longer hours ($\beta_1 = 0.186$). They are able to locate short trips (e.g., $\beta_7 = -0.021$) with significantly less cruising time across all times of a day (e.g., $\beta_3 = -0.096$), in both high- and low-demand areas. They also tend to be less concentrated in cruising route selection ($\beta_{11} = -0.195$).

We present the interaction of the immediate adoption impact and a driver's skill level ($\Delta\beta_k$) in column (4). Driving skill is a standardized measure of hourly earnings in the initialization window. Take a highly skilled driver at level +1 (one standard deviation above the mean) and a low-skill driver at level −1 (one standard deviation below the mean). We find very different patterns of the immediate adoption impacts between high- and low-skill drivers. Instead of further reducing the number of trips and working hours as high-skill drivers did, low-skill drivers worked significantly longer hours ($0.089 = -0.046 - 0.135 \times (-1)$) and took significantly more trips ($0.258 = -0.031 - 0.289 \times (-1)$). It relates to the way taxi drivers take advantage of mobile hailing apps. Low-skill drivers tended to use the apps to reduce cruising time at all times in both high- and low-traffic areas (i.e., $-0.291 = -0.153 + 0.138 \times (-1)$). They were less concentrated with cruising areas ($0.085 = 0.261 + 0.176 \times (-1)$); their trip distances also dropped significantly (e.g., $-0.119 = 0.048 + 0.167 \times (-1)$). On the contrary, highly skilled drivers barely reduced cruising time after adopting the apps (i.e., $-0.015 = -0.153 + 0.138 \times (1)$); instead, they selected longer trips given the revealed drop-off locations of trip requests (e.g., $0.215 = 0.048 + 0.167 \times (1)$). It is notable that high- and low-skill drivers take different strategies to improve the relative ratio of driving over cruising time with the help of mobile hailing apps.

Estimates in column (5) refer to the extent to which taxi drivers who chose not to adopt mobile hailing technology faced competition from the peers who adopted the apps. Interestingly, we find that none of the estimates in column (5) are statistically significant. This is evidence that an increasing market adoption rate of mobile hailing technology did not affect the driving behaviors of those who chose not to adopt the mobile hailing technology.

The adoption impact on driving behaviors may change over time as more and more taxi drivers adopt mobile hailing technology. Column (6) speaks to the extent to which the driving behavior changes ($\Delta\alpha_k$) evolve as a function of the market adoption rate. We highlight the findings that as the market adoption rate increases, the cruising-time reduction dissipates (e.g., $\Delta\tau_3 = 0.462$), whereas the selection into longer distance trips gets more pronounced (e.g., $\Delta\tau_7 = 0.398$). This pattern holds across all times of day in both high- and low-traffic areas.

Now let us look at the pattern by driver skill. Take a 50% market adoption rate as an example. An average-skill taxi driver who adopted mobile hailing technology would spend approximately the same amount of time as he or she did before (e.g., $0.078 = -0.153 + 0.462 \times 0.50$) looking for longer and larger-fare trips (e.g., $0.247 = 0.048 + 0.398 \times 0.50$). They would use the mobile apps to select trips. Trip selection becomes a dominant performance improvement strategy for highly skilled drivers as the market adoption rate goes up. At a 50% market adoption rate, a highly skilled driver at level +1 who adopted mobile hailing apps would spend significantly more time (e.g., $0.216 = -0.153 + 0.138 + 0.462 \times 0.50$) searching for longer trips (e.g., $0.414 = 0.048 + 0.167 + 0.398 \times 0.50$). Even low-skill drivers who tried to merely reduce cruising time at the early stage of adoption appeared to engage in both idle-time reduction (e.g., $-0.06 = -0.153 - 0.138 + 0.462 \times 0.50$) and selection of longer trips (e.g., $0.08 = 0.048 - 0.167 + 0.398 \times 0.50$).

To our knowledge, this is the first direct empirical evidence of the value of mobile hailing technology. We show that drivers' adoption of mobile hailing technology is associated with driving pattern changes even without surge pricing. The mobile hailing technology provides real-time transparent information on pickup and the drop-off locations. However, information transparency is a double-edged sword. It may boost adopted drivers' performance at the expense of a welfare loss for small-fare, short-trip riders. Our results echo the general public's concerns about the increasing difficulty of getting taxi service since the introduction of mobile hailing technology.[7]

6.2. Mobile Hailing Technology Adoption Decision

A legitimate concern is whether the results may suffer from the self-selection of adoption. This may lead to the overestimated adoption impacts of mobile hailing technology if the unobserved shocks to driving behaviors are positively correlated with the adoption decision. For instance, a driver who chooses to adopt

Table 4. Parameter Estimates of Adoption Probability

	Estimate	95% CI
Intercept	**−2.433**	(−2.446, −2.423)
Skills	−0.002	(−0.006, 0.002)
Diffusion $R_{t-1} \times (1 - R_{t-1})$	**1.212**	(1.159, 1.280)
Number of neighbor adoptions at time $t-1$ (ln)	**0.010**	(0.006, 0.015)
Number of interacted adoptions at time $t-1$ (ln)	**0.014**	(0.007, 0.023)
Unobserved heterogeneity standard deviation	**0.090**	(0.087, 0.093)
Log-likelihood	−1,860,135	

Notes. The parameters fit the 2,106 taxi panelists as well as 285 survey respondents. The bold indicates that the 95% credible interval does not contain zero.

Table 5. Variance (Diagonal) and Correlation (Off-Diagonal) Matrix of Unobserved Individual Heterogeneity ζ_{ik}^{W} and ζ_{i}^{A}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *Working hours* (ln)	**0.025**											
(2) *Number of trips* (ln)	**0.399**	**0.050**										
(3) *Cruise time, rush hour, high traffic*	**0.108**	**−0.364**	**0.065**									
(4) *Cruise time, non–rush hour, high traffic*	**0.173**	**−0.385**	**0.623**	**0.047**								
(5) *Cruise time, rush hour, low traffic*	**0.110**	**−0.404**	**0.626**	**0.492**	**0.066**							
(6) *Cruise time, non–rush hour, low traffic*	**0.154**	**−0.428**	**0.508**	**0.715**	**0.573**	**0.051**						
(7) *Trip distance, rush hour, high traffic*	0.027	0.027	**0.279**	**0.263**	**0.324**	**0.297**	**0.066**					
(8) *Trip distance, non–rush hour, high traffic*	0.046	**−0.559**	**0.272**	**0.268**	**0.303**	**0.282**	**0.783**	**0.059**				
(9) *Trip distance, rush hour, low traffic*	0.017	**−0.561**	**0.270**	**0.247**	**0.340**	**0.291**	**0.728**	**0.751**	**0.074**			
(10) *Trip distance, non–rush hour, low traffic*	0.045	**−0.577**	**0.267**	**0.267**	**0.317**	**0.303**	**0.745**	**0.822**	**0.780**	**0.063**		
(11) *Cruising route concentration* (ln)	**−0.155**	**−0.432**	**0.206**	**0.272**	**0.287**	**0.350**	**0.205**	**0.198**	**0.208**	**0.202**	**0.070**	
(12) *Adoption tendency*	0.011	−0.006	−0.005	−0.005	−0.005	−0.002	0.012	0.015	0.012	0.015	0.012	**0.008**

Note. The bold font indicates that the 95% CI does not contain zero.

the mobile hailing apps may expect a higher return of adoption. Table 4 reports the factors in the adoption decision of mobile hailing technology. There is limited heterogeneity in the baseline adoption tendency, as the standard deviation of the unobserved heterogeneity is relatively smaller compared with the magnitude of the baseline adoption tendency. The driving skill indicator does not affect adoption tendency. The diffusion factor $R_{t-1} \times (1 - R_{t-1})$ is a significant driver of adoption. The significantly positive coefficient is consistent with the new technology diffusion process. Both the two exclusion variables, the number of adopters among neighboring taxi drivers within two kilometers, and the number of adopters among randomly encountered taxi drivers have significant coefficients with the expected positive signs. It implies that mobile hailing technology adoption is affected via offline word of mouth between taxi drivers that live close by and via the information shared at random social encounters.

Additionally, we allow the unobserved individual heterogeneity ζ_{ik}^{W} in each driving Equation (2) to be correlated with the unobserved heterogeneity ζ_{i}^{A} in the adoption tendency Equation (5). The estimated correlation structure speaks to whether there is an unobserved shock that drives the driving behaviors as well as the adoption decision. The off-diagonal correlations in Table 5 show that there is no significant correlation between the unobserved heterogeneity in the driving behaviors and that in the adoption tendency. It suggests that self-selection is very limited in our context and that the estimated driving behavior changes in Table 3 are not confounded with the adoption process. We do find that the unobserved error terms of the 11 driving behaviors have statistically significant correlations. For example, the cruising route concentration index is positively related to the trip distance. It implies that longer trips tend to be positively correlated with certain cruising route. However, longer trips also seem to be associated with more searching for the next trip. Even with the apps' revealed origin and destination information, there is a tradeoff between the large fares out of a long trip and the amount of time looking for the next trip.[8]

We have also controlled for the potential endogeneity, as the adoption rate R_t and driving performance W_{ikt} can be subject to common market shocks ξ_{kt}, for example, a traffic censor order due to a leadership visit to Beijing. We show in Table 6 that the one-period-lagged market adoption rate R_{t-1} has a positive and significant coefficient with the current-period adoption rate R_t. The other instrumental variable, the Baidu search index of smartphones, however, is not significantly related to the current-period market adoption rate R_t.[9] We suspect that this could be because of a weak link between the search indicator and the market-level mobile app adoption rate, as taxi drivers are not the only target segment of smartphones. Similarly, we look at the estimated variance–covariance matrix in Table 7 for evidence of endogeneity between market adoption and driving behaviors. As can be seen, there is no evidence of a common market shock that drives the market adoption rate R_t and driving behaviors W_{ikt} beyond the included market-specific control variables X_t.

6.3. Hourly Earnings Decomposition

Given the recovered adoption decisions, we evaluate the effect of mobile hailing technology adoption on taxi drivers' productivity in the measure of hourly earnings. We first link the hourly earnings to the 11 driving behaviors and quantify the importance of each behavior to hourly earnings. Next, we quantify the changes in hourly earnings as a result of changes in the 11 driving behaviors after mobile app adoption.

In the first step, we regress the logarithm of hourly earnings on the 11 driving behaviors along with a set of control variables through panel regression. The unit of analysis is at the driver-week level. The driving behaviors and the productivity measure of hourly earnings could be driven by the same unobserved

Table 6. Parameter Estimates of Market Adoption Rate

	Estimate	95% CI
Intercept	0.047	(−0.328, 0.456)
One-period lag market adoption rate	**0.943**	(0.250, 1.587)
Search smartphone	−0.069	(−1.075, 1.110)
Market shock standard deviation	**0.385**	(0.335, 0.466)

Note. The bold indicates that the 95% credible interval does not contain zero.

factors. We use the one-period lag of all the 11 driving behaviors as instruments to control for endogeneity. Random effects are also included to control for individual heterogeneity. Table 8 provides the results of a random effect panel instrumental variable regression. It is shown that 70% of within-individual over-time variations and 76% of across-individual variations in hourly earnings can be explained by the 11 driving behaviors. All the coefficients of the 11 measures are significant and have signs consistent with expectations. Efficient search of longer trips during nonrush time periods is more important than that during the rush time periods. An excellent taxi driver beats a mediocre one in the ability to locate longer trips during the low-demand nonrush time periods.

Given the inferred individual driver's adoption period, we obtain the estimated adoption impact on the 11 driving behaviors for each individual given his driving skill and adoption time. We extend the adoption impacts on the driving behaviors to hourly earnings based on the recovered relationship between hourly earnings and the driving behaviors. This allows us to decompose the increase in hourly earnings to each of the 11 driving behaviors.

Table 9 shows the average decomposition effect across all the taxi drivers. We find that mobile hailing technology adoption is associated with an average 6.8% increase in hourly earnings. Overall, 6.2% out of the 6.8% hourly earnings improvement following the adoption of mobile hailing apps comes out of trip selection in favor of longer and larger-fare trips. Specifically, the sorting behavior in nonrush periods and high-traffic areas contributed 2.9%, whereas the selection in nonrush periods and low-traffic areas contributed 2.0%. This is followed by a 0.5% contribution from trip selection during rush time periods in high- and low-traffic areas, respectively. The second important source of hourly earnings increase comes from the increase in the number of trips (1.4% out of 6.8%). It is mainly driven by the low-skill drivers, who took significantly more trips after adopting the apps. This pattern persists as the market adoption rate goes up. The next source of hourly earnings increase comes from the cruising-time reduction. However, only a very small proportion of the hourly earnings increase (0.5% out of 6.8%) is related to cruising-time reduction after the app adoption. The cruising-time reduction concentrates in high-traffic areas. The adoption-induced daily working hour increase does not significantly relate to the hourly earnings. Direction-wise, the increase in working hours negatively affects the hourly earnings (−1.2% out of 6.8%). The changes in cruising route concentration level has a very minimal and nonsignificant impact on hourly earnings (−0.1% out of 6.8%). Overall, the 6.8% hourly earnings increase is approximately equivalent to an extra CNY 750 monthly income to an average taxi driver. This is a significant number compared with the monthly CNY 5,200 fleet rental fee.

It is interesting to see that the effect of trip selection dominates the effect of cruising-time reduction when we look at an average taxi driver across different times of a day and areas of various traffic density. Yet, we suspect that driving skills (before adoption) and market conditions may moderate the way taxi drivers take advantage of the revealed pickup and drop-off locations from the mobile hailing technology.[10] To assess the moderators, we look at the low- and high-skill taxi drivers at the median split of the normalized driving skill index (E_i). We also distinguish between the thin and thick markets, where the thin markets are

Table 7. Variance (Diagonal) and Correlation (Off-Diagonal) Matrix of Market Shocks ξ_{kt}^{W} and ξ_{t}^{R}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *Working hours* (ln)	**0.175**											
(2) *Number of trips* (ln)	0.061	**0.170**										
(3) *Cruise time, rush hour, high traffic*	0.004	−0.010	**0.178**									
(4) *Cruise time, non–rush hour, high traffic*	−0.008	−0.017	0.012	**0.173**								
(5) *Cruise time, rush hour, low traffic*	0.001	−0.007	0.001	0.006	**0.176**							
(6) *Cruise time, non–rush hour, low traffic*	0.006	−0.002	0.011	−0.002	0.005	**0.172**						
(7) *Trip distance, rush hour, high traffic*	0.007	−0.001	0.006	−0.007	0.012	0.009	**0.177**					
(8) *Trip distance, non–rush hour, high traffic*	0.015	0.010	−0.001	−0.019	−0.005	0.011	0.019	**0.178**				
(9) *Trip distance, rush hour, low traffic*	0.005	−0.001	−0.005	0.013	0.002	−0.015	0.022	0.006	**0.177**			
(10) *Trip distance, non–rush hour, low traffic*	−0.002	−0.016	−0.011	0.015	−0.001	−0.007	−0.009	−0.010	−0.003	**0.172**		
(11) *Cruising route concentration* (ln)	−0.032	−0.025	0.023	0.009	0.028	0.019	0.012	−0.007	0.005	0.004	**0.206**	
(12) *Adoption tendency*	0.004	−0.004	−0.005	0.008	−0.001	−0.001	−0.004	−0.013	0.007	0.008	−0.002	**0.155**

Note. The bold font indicates that the 95% CI does not contain zero.

Table 8. Regression of Log Hourly Earnings on Driving Behavior Measures

	Estimate	95% CI
Daily work hours (ln)	**−0.612**	(−0.627, −0.596)
Log *daily trips* (ln)	**0.664**	(0.650, 0.678)
Cruising time index		
Rush hour, high-traffic area	**−0.016**	(−0.020, −0.013)
Non–rush hour, high-traffic area	**−0.090**	(−0.099, −0.081)
Rush hour, low-traffic area	**−0.016**	(−0.019, −0.012)
Non–rush hour, low-traffic area	**−0.047**	(−0.053, −0.040)
Trip distance index		
Rush hour, high-traffic area	**0.038**	(0.034, 0.042)
Non–rush hour, high-traffic area	**0.197**	(0.187, 0.207)
Rush hour, low-traffic area	**0.039**	(0.035, 0.042)
Non–rush hour, low-traffic area	**0.142**	(0.134, 0.150)
Cruising concentration (ln)	**−0.046**	(−0.054, −0.039)
Control variables	Yes	
Within-individual R^2	0.696	
Between-individual R^2	0.759	

Notes. We include a fare change dummy, the Chinese New Year and National Day, and the numbers of days in a week that are above 30°C, below 5°C, rainy, snowy, foggy, and smoggy, respectively, as control variables. The bold indicates that the 95% credible interval does not contain zero.

defined as the nonrush time periods and low-traffic areas, and the thick markets as rush time periods and high-traffic areas. We follow the same two steps as explained previously. The only difference is that this time we focus on the hourly earnings of a specific type of taxi driver in either thin or thick markets rather than the average hourly earnings in a day. We regress the market-specific hourly earnings of each driver in each week on the same set of driving behavior variables and the control variables. Next, we look at how the adoption-induced driving behavior changes will pass on to the hourly earnings for low- and high-skill drivers in thin and thick markets.

Table 10 presents the relative importance of the two sources of hourly earnings increase, cruising-time reduction and trip selection, by driver skill and market condition. We find that, regardless of market conditions, trip selection in favor of longer trips is the dominant strategy for highly skilled drivers in improving their hourly earnings. This is reasonable because the estimates in Table 3 suggest that before adoption, highly skilled drivers were significantly more effective at cruising and spent less time in locating future trips. There could be a ceiling effect on further reducing their cruising time. Given that the key factor in determining the hourly earnings is the relative ratio of driving over cruising time, highly skilled drivers improve their performance by selecting the longer trips to effectively increase the ratio regardless of market conditions.

We now turn to low-skill drivers. We find that cruising-time reduction is the primary mechanism of productivity gains for low-skill drivers in thick markets: A dominant 74% increase in hourly earnings is due to the ability to reduce cruising time, whereas the remaining 26% is out of selection in favor of longer trips. Yet, the two mechanisms are almost equally important to low-skill drivers in thin markets (44% versus 56%). Low-skill drivers started with less efficient search of potential riders and took longer to locate trips. Thick markets offer more nearby trip requests compared with thin markets. The information role of mobile hailing applications is limited in thin markets with low demand, where the nearest by request for pickup may still be kilometers away. Therefore, low-skill drivers cannot simply rely on cruising-time reduction to improve their ratio of driving over cruising time. They also engage in selection of longer trips to improve the hourly earnings.

Table 9. Impact of Mobile Hailing Technology Adoption on Driver's Hourly Earnings

	% estimate	95% CI
% increase in hourly earnings	**6.823**	(5.268, 7.990)
Decomposition of the % increase into driving behaviors		
Daily working hours	−1.199	(−2.691, 0.251)
Daily number of trips	**1.394**	(0.133, 2.786)
Cruising time overall	**0.528**	(0.227, 0.806)
Rush hour, high-traffic area	**0.094**	(0.047, 0.155)
Non–rush hour, high-traffic area	**0.268**	(0.047, 0.467)
Rush hour, low-traffic area	0.042	(−0.009, 0.090)
Non–rush hour, low-traffic area	0.108	(−0.001, 0.235)
Passenger distance overall	**6.190**	(5.194, 6.853)
Rush hour, high-traffic area	**0.493**	(0.380, 0.607)
Non–rush hour, high-traffic area	**2.867**	(2.386, 2.335)
Rush hour, low-traffic area	**0.536**	(0.418, 0.670)
Non–rush hour, low-traffic area	**2.011**	(1.490, 2.378)
Cruising concentration	−0.092	(−0.202, 0.021)

Note. The bold indicates that the 95% credible interval does not contain zero.

Table 10. Relative Importance of the Sources of Hourly Earnings Increase by Driver Skill Type and Market Condition

	Cruising time reduction	Trip selection	Hourly earnings change
Low-skill driver			
Thick market	74.40%	25.60%	100%
	0.93 (0.70, 1.16)	0.32 (0.11, 0.56)	1.25 (0.94, 1.53)
Thin market	44.35%	56.45%	100%
	0.55 (0.43, 0.68)	0.70 (0.46, 0.95)	1.24 (0.98, 1.50)
High-skill driver			
Thick market	−24.41%	124.41%	100%
	−0.52 (−0.84, −0.24)	2.65 (2.32, 3.02)	2.13 (1.64, 2.53)
Thin market	−13.04%	113.04%	100%
	−0.54 (−0.73, −0.27)	4.68 (4.36, 5.13)	4.14 (3.72, 4.57)

Notes. Numbers in the first row for each item (with percent symbol) represent the relative importance of the two mechanisms of improving hourly earnings. Numbers in the second row for each item represent the mean estimate of the hourly earnings percentage change. The 95% confidence intervals are provided in parentheses.

6.4. Adoption Impacts on Hourly Earnings Over Time

The change-point model allows us to quantify the immediate adoption impacts on the productivity measure of hourly earnings at different market adoption rates. The estimated market adoption rate increased from 0% at the end of January 2013 to 53% at the end of June 2014. Figure 5 plots the immediate adoption impacts against our observation window of 18 months. It shows that the immediate adoption impact decreases over time as the market adoption rate increases. The shaded area indicates a 95% confidence interval. An average driver who adopts mobile hailing apps at the beginning of February 2013 will have a more than 10% immediate increase in hourly earnings, whereas the average driver who adopts mobile hailing apps in March 2014 will not see a significant increase in his hourly earnings.

Given the recovered adoption decisions, we perform a synthetic control analysis between taxi drivers who chose to adopt and those who chose not to adopt the mobile hailing technology. Synthetic control has been applied in various marketing contexts to recover the treatment effect over time (Chesnes et al. 2017, Tirunillai and Tellis 2017). We use a weighted average of nonadopters as a synthetic control to the adopters and investigate the long-term adoption impacts on hourly earnings over time. The benefit of building this synthetic control group is that the adopters' preadoption hourly earnings can be very well approximated by an optimally weighted combination of the nonadopters (Abadie and Gardeazabal 2003, Abadie et al. 2015).

Figure 5. (Color online) Immediate Adoption Impact on Hourly Earnings at Different Times

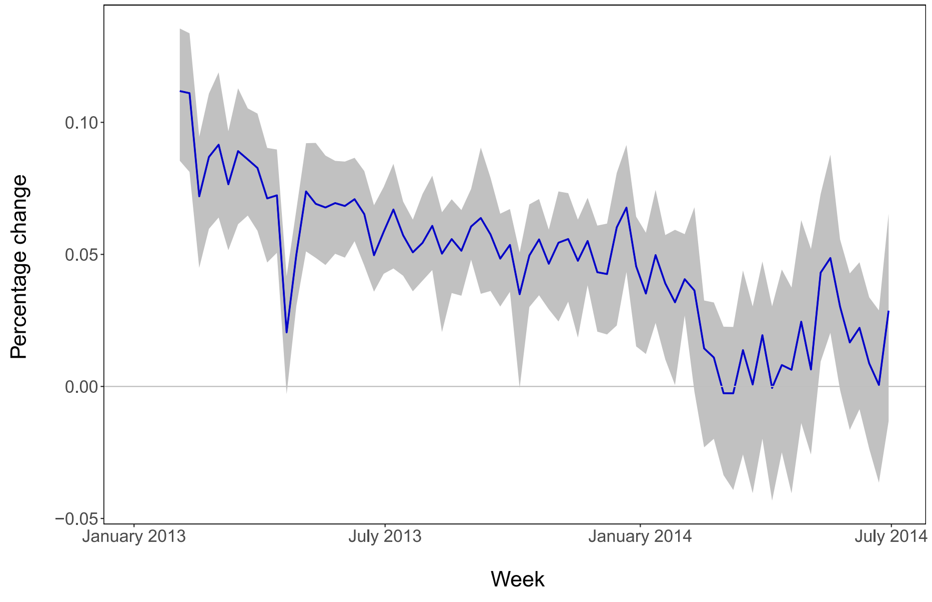


Figure 6 shows the percentage difference in the hourly earnings between the adopted and nonadopted taxi drivers over time. As can be seen, the hourly earnings between the two groups are closely matched before the adoption period. After the adoption, the adopters' hourly earnings are about 6%–7% above those of the synthetic control group of nonadopters. This number cross-validates the parametrically estimated 6.8% increase in hourly earnings in Table 9. The synthetic control approach also shows that the adoption impact on hourly earnings persists for approximately 20 weeks and gradually disappears after 40 weeks.

6.5. Mobile Hailing App Usage and Consumer Welfare

Although our study focuses on the impact of the new mobile innovation on taxi drivers, it is important to look into its impact on consumers. A consumer can benefit from the new technology via either shorter waiting periods or more taxi supply. The technology could also hurt a consumer because of taxi drivers' trip-sorting behaviors.

Table 11 provides the numbers of realized trips and trip distances in June 2013 and June 2014. It shows that the average daily number of realized trips is $5.592 = 1.794 + 2.640 + 1.158$ during rush hours in June 2013 and $5.442 = 1.684 + 2.580 + 1.178$ during rush hours in June 2014. The average daily number of realized trips is $13.653 = 4.044 + 7.493 + 2.116$ during nonrush hours in June 2013 and $12.949 = 3.533 + 7.155 + 2.241$ during nonrush hours in June 2014. We also group trips by distance using the same cutoffs of 3 and 15 kilometers, as in the trip fare scheme. The daily numbers of short and medium trips (≤15 kilometers) significantly drop, whereas the daily number of long trips (≥15 kilometers) significantly increases at all times. In terms of the proportion, the percentage of long trips increases from 20% to 22%. In addition, the average trip distance significantly increases for both the medium and long trips (≥3 kilometers). Taking both trip number and trip distance into account, this suggests that trips are redistributed toward long distances across all the times within a day.

Our results imply that long-trip riders get easier access to the taxi service after the introduction of mobile hailing technology, whereas the short-trip riders are more likely to be declined because of app-enabled trip-selection behaviors. We cautiously note that we do not explicitly model the rider-side demand. Table 11 provides only the indirect evidence regarding consumer welfare under the new mobile hailing technology. We leave it to future research to explicitly model the demand-side trip requests together with the supply-side order-taking behaviors.

7. Conclusion

Mobile hailing technology has brought unprecedented changes to the operations of the taxi industry. Understanding the economic impact of this latest innovation is of great importance to both industry practitioners and the academic audience. In this paper, we provide the first (to our knowledge) empirical evidence on the extent to which mobile hailing technology affects taxi driving behaviors. We develop a change-point model to investigate driving behavior changes following the adoption of mobile hailing technology

Figure 6. Long-Term Adoption Impact on Hourly Earnings

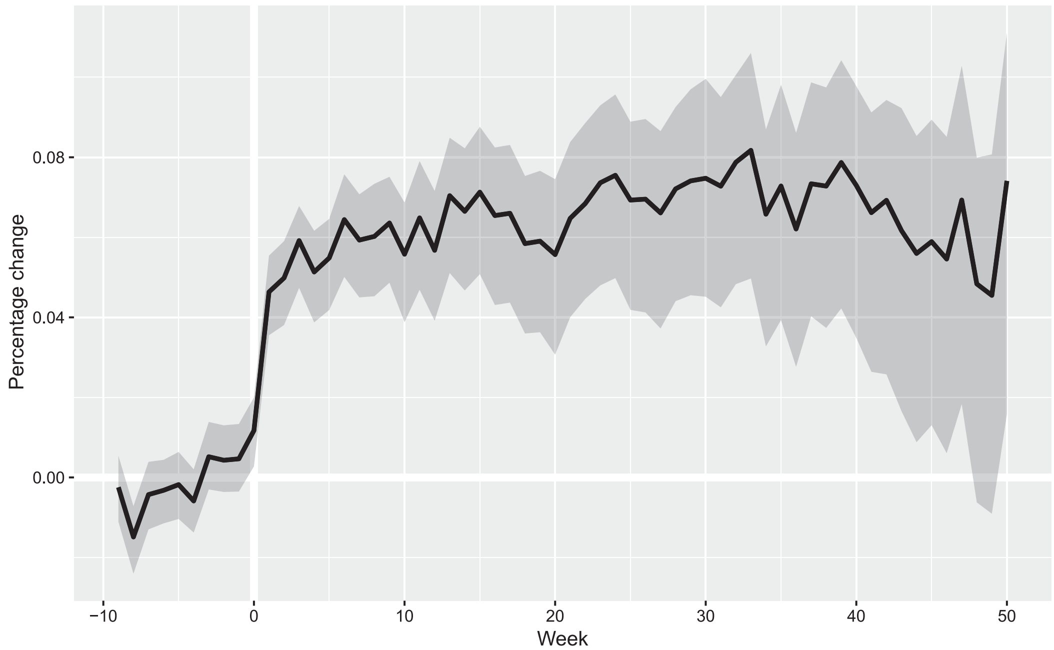


Table 11. Realized Trips by Distance and Hour of Day

	June 2013			June 2014		
	Short trips	Medium trips	Long trips	Short trips	Medium trips	Long trips
Average daily trips						
Rush hours	1.794	2.640	1.158	1.684***	2.580***	1.178***
Nonrush hours	4.044	7.493	2.116	3.553***	7.155**	2.241***
Average trip distance						
Rush hours	1.760	7.190	22.682	1.755	7.275***	22.715**
Nonrush hours	1.746	7.223	22.856	1.740	7.298***	23.097**

Notes. The average daily number of realized trips is 5.592 = 1.794 + 2.640 + 1.158 in rush hours in June 2013 and 5.442 in rush hours in June 2014. The average daily number of realized trips is 13.653 in nonrush hours in June 2013 and 12.949 in nonrush hours in June 2014. Short, medium, and long trips refer to the trips less than 3 kilometers, between 3 and 15 kilometers, and above 15 kilometers, respectively. We refer to 7:00–9:00 a.m. and 5:00–7:00 p.m. as rush hours.

$^{**}p < 0.05$ and $^{***}p < 0.01$ for the same variable comparison between June 2013 and June 2014.

and apply it to a novel data set with minute-level driver geolocation records in a metropolitan market.

Mobile hailing technology adoption is associated with an average hourly earnings increase of 6.8%, which is equivalent to an extra CNY 750 monthly income. This is a significant number compared with the monthly CNY 5,200 fleet rental fee, which exerts the most burden on taxi drivers. Our decomposition shows that for an average taxi driver who adopted mobile hailing apps, 6.2% out of the 6.8% hourly earnings improvement comes from trip selection in favor of longer and larger-fare trips, whereas cruising-time reduction contributes only 0.5% of the 6.8% hourly earnings increase.

In addition, we show that the relative importance of the two mechanisms of cruising-time reduction and trip selection depends on driver skills and market conditions. Highly skilled drivers who were able to effectively locate trips before the introduction of mobile hailing technology improve their performance with selection toward longer trips in both thick and thin markets, as there is a ceiling effect on further reducing their cruising time. When it comes to low-skill drivers, cruising-time reduction is the primary mechanism of productivity gains in a thick market, whereas the two mechanisms of cruising-time reduction and trip selection are almost equally important to low-skill drivers working in thin markets, where the sparse local demand limits the information role of mobile hailing applications. Therefore, low-skill drivers cannot simply rely on cruising-time reduction to improve their ratio of driving over cruising time and thereby increase hourly earnings.

Although our study focuses on the impact of the mobile innovation on taxi drivers, it is also important to explore its impact on consumers. We show that there is no market expansion effect of the introduction of mobile hailing technology, in the sense that the number of realized trips did not increase. Rather, the realized trips were redistributed toward long distances.

Trip selection is potentially an unintended and undesirable outcome in terms of consumer welfare and fairness concerns. The phenomenon we document applies not only to the taxi market but also to the ride-sharing market of private vehicles that was later introduced. We suggest that the remedies are not difficult or burdensome. Waiting to reveal a rider's destination until a trip is accepted is a simple and feasible choice. Almost all the mobile hailing and the majority of the ride-sharing applications in China provide drivers with passengers' pickup and drop-off locations. In fact, there is a widespread concern that it has become more difficult to find a cab for short trips after the launch of mobile hailing technology (Langfitt 2014). Most recently, in December 2017, four years after the introduction of mobile hailing applications in China, regulators in Shanghai ordered the apps to block passengers' destination information before orders are accepted to prevent cherry-picking.

Our findings should be interpreted based on limitations inherent to our context. For example, although our research context offers a clean enough setting to observe taxi driver behavioral changes after the introduction of mobile hailing technology, it is also a setting without the existence of Uber-type ride-sharing services. The lack of competition and shortage of taxi supply possibly explain why app-using drivers demonstrate trip-sorting behaviors. The Uber-type ride-sharing service may change the supply–demand relationships in the market. It is an open question as to how the entry of ride sharing may impact the driving behaviors and hourly earnings of taxi drivers.

An important data limitation is that we do not observe the adoption timing and have to infer the adoption decision from the observed changes in the driving dimensions, including cruising time between trips, trip distance, cruising area concentration level, daily number of trips, and daily working hours. Future research could acquire driver-level app-adoption data from mobile hailing companies and compare the findings with ours. However, the value of incorporating the app company data comes at a cost. The mobile hailing companies have driving behavior data only after taxi drivers register with the apps. The historical driving behaviors before the adoption window are unavailable, as is the information regarding the nonadopters and the street-hail trips that are not booked though the app.

A further limitation of our research is that we focus entirely on the supply side of taxi drivers. We do not have access to detailed rider request information. We acknowledge that it is important to fully evaluate rider welfare before and after the introduction of mobile hailing technology. We leave it to future research, when information for both demand and supply is available.

As surge pricing has become a standard feature in many mobile hailing apps today, it could be one of the most important future research areas. Surge pricing could play a key role in market demand and driver labor supply. In our context, there is no surge pricing at any period in our observation window. However, we do accommodate the differences in the changes of driving behaviors between rush and nonrush time periods and in high- versus low-traffic areas. It is possible that drivers may develop different driving strategies under surge pricing. Future work that accurately quantifies consumer price elasticity and driver labor supply would provide a basis to evaluate the social welfare impact of surge pricing. Data sets that include consumer-side order requests, driver-side order taking, geolocation driving records, and surge pricing scheme are a great fit for this topic.

Acknowledgments

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Endnotes

[1] See http://www.tour-beijing.com/taxi/#.W3ibk-hKj-g.

[2] CNY is the currency code for the Chinese yuan. In January 2013, CNY 1 = USD 0.16.

[3] The two largest taxi-hailing mobile apps, Didi Dache and Kuaidi Dache, completed a strategic merger in 2015. The merged company accounted for an 83.2% market share of active mobile hailing users in China. For a history of the company, see https://www.techinasia.com/didi-chuxing-history.

[4] There is no official statement from the leading companies on the rationale of the disclosure of destination information. We speculate that they followed the practice of the telephone taxi booking system, where both pickup and drop-off locations are required.

[5] HDBSCAN is a nonsupervised learning algorithm. HDBSCAN uses mutual reachability distance to capture the spatial density rather than just a distance measure from the cluster centroid. We do not specify the number of clusters beforehand; instead, only the minimum data point per cluster is required. Our model estimation results are robust to different minimum-cluster parameters. The hdbscan package in Python is used to produce the clustering (McInnes et al. 2017).

[6] We use panel regressions to regress the focal driver's driving behaviors on his or her local neighbors' driving behaviors. We also include individual and week fixed effects and all the control variables in Equation (5). The local neighbors' driving behaviors have nonsignificant coefficients in 9 out of the 11 driving behavior measures, with the other 2 marginally significant ($t = 2.1$).

[7] See https://maximumridesharingprofits.com/cant-uber-drivers-see-passengers-destination-accepting-trip/.

[8] Statistically speaking, a one-kilometer increase in the trip distance is associated with an average 0.29-minute increase in cruising time for the next trip. The marginal earnings rate (for trips longer than three kilometers) is still higher than the average hourly earnings in our sample. Thus, long trips are still more preferable on average.

[9] We also tried other search indices on smartphones, such as a search of Huawei-brand smartphones, and found similarly insignificant results.

[10] We thank the reviewer team for this important suggestion.

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