Learning Individual Behavior Using Sensor Data: The Case of GPS Traces and Taxi Drivers

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The ubiquitous deployment of mobile and sensor technologies has led to both the capacity to observe human behavior in physical (offline) settings as well as to record it. This provides researchers with a new lens to study and better understand the individual decision processes that were previously unobserved. In this paper, we study decision making behavior of 11,196 taxi drivers in a large Asian city using a rich data set consisting of 10.6 million fine-grained GPS trip records. These records include detailed taxi GPS trajectories, taxi occupancy data (i.e., whether a taxi was occupied with a passenger or was vacant) and taxi drivers' daily incomes. This capacity to use data where occupancy of the taxi is known is a distinctive feature of our data set and sets this work apart from prior work which has attempted to study driver behavior. The specific decision we focus on pertains to actions drivers take to find new passengers after they have dropped off their current passengers. In particular, we study the role of information derivable from the GPS trace data (e.g., where passengers are dropped off, where passengers are picked up, longitudinal taxicab travel history with fine-grained time stamps) observable by or made available to drivers in enabling them to learn the distribution of demand for their services over space and time. We conduct our study using a heterogeneous Bayesian learning model. We find strong heterogeneity in individual learning behavior and driving decisions, which is significantly associated with individual economic outcomes. Drivers with higher incomes benefit significantly from their ability to learn from not only demand information directly observable in the local market, but also aggregate information on demand flows across markets. Interestingly, our policy simulations indicate information that is noisy at the individual level becomes valuable after being aggregated across various spatial and temporal dimensions. Moreover, the value of information does not increase monotonically with the scale and frequency of information sharing. Finally, our study has important welfare implications in that efficient information sharing leads to an income increase among all drivers, instead of a redistribution of income between different types of drivers. Our work allows us not only to explain driver decision making behavior using these detailed behavioral traces, but also to prescribe information sharing strategy for the firm in order to improve the overall market efficiency.

1. Introduction

The ubiquitous deployment of pervasive, interconnected, smart mobile and sensor technologies have led to both the capacity to observe human behavior in physical (offline) environments as well as to record it. We see such examples in hospitals, shopping malls, airports, schools, cities, and many other contexts in today's world. Such emerging sources of digitized human behavioral trace data provide researchers with a new lens to study and understand the individual behavior that was previously unobserved. It helps us develop a holistic view of individual decision-making processes and to unravel the complexity of human behavior patterns. Recent studies have shown that by examining the human trace data recorded through mobile sensors, researchers can better understand the dynamic social interactions of humans and idea flows in society (Pentland (2014)), and individuals' real-time social contexts (e.g., whether an individual appears in a group with others or alone by him/herself) (Liu et al. (2013b), Sen et al. (2014)). Moreover, by combining analytical insights from the observational data of human behavioral traces with randomized user experiments, we are able to design and implement policy interventions to improve the efficiency of human decision-making. For example, a recent large-scale field experiment has demonstrated that by mining shopping-mall customers' mobile trajectory data at a granular level, retailers can learn consumer preferences and design more effective mobile advertising strategy (Ghose et al. (2015)).

Despite the increasing availability and size of human trace data, the extraction, analysis, and understanding of the multi-dimensional, dynamic and heterogeneous nature of individuals' behavior from such information is challenging. *First*, individuals' behavioral patterns tend to be highly context-dependent. It is challenging to understand the real-time social, spatial and temporal contexts to which users are exposed during decision making. *Second*, users' decision-making processes are often dynamic and interactive. It is critical to learn from the digital trace data what information signals a user likely received prior to the user's decision-making process, and what action the user has taken in response to each different information signal. *Third*, users are heterogeneous in nature. As a result, we need to understand the heterogeneous responses to information from different users, as well as the associated outcomes. This step will help us understand the major drivers of heterogeneity in individual behavior and the discrepancy in observed outcomes in markets. *Finally*, and importantly, the manner in which potential inefficiencies can be addressed using insights from such large-scale, granular-level information is under-investigated. In particular, how can we better design policies to improve individual decision making and market efficiency? In this study, we focus on addressing these challenges in learning from human digital traces in the offline settings.

Given the importance and ubiquity of urban transportation, we study the behavior of taxi drivers. Despite the entry of ride sharing platforms such as Uber, the taxi industry is a major component of urban transportation infrastructure. According to a recent report by Brennan (2014), every year approximately 700 million passengers are transported by taxicabs in the US, generating $16 billion in revenues. However, the taxi industry has been notorious for its inefficiency due to high search frictions in the market and inefficient information sharing among drivers or passengers, leading to a lack of efficient matching between supply and demand. The mismatch between taxi demand and supply has become severe in many big cities. For example, in New York City, the 2014 Taxicab Fact Book[1] points out that average taxi occupancy during weekday rush hours is only 56%; moreover, passengers have an especially difficult time hailing taxis during shift-change time and in bad weather. Similar phenomena are also observed in other large cities in other countries. For example, in Beijing, around 30% of people spent more than 20 minutes waiting for a taxi in 2015.[2] On the other hand, a taxi's average monthly empty-car distance reached 2,400km compared to an occupied distance of 5,088km, which indicates that on average about one third of total driving distance for taxis is allocated not for serving passengers but for searching for passengers.

Such inefficiency in the taxi market has attracted the attention of industry as well as academia. Recent work has attempted to study the matches made between drivers and passengers revealed from the taxis' pick-up and drop-off data to explain the market inefficiency under regulation. For example, using the NYC yellow medallion taxi data, Salz et al. (2015) studied the effect of regulations on aggregate city-level taxi service and demand. Buchholz (2015) analyzed the same NYC taxi data to study the dynamic equilibrium effects of regulations on spatial search frictions and welfare. He found significant search frictions in the taxi industry, which lead to a reduction in welfare by $422M or 62% per year. Meanwhile, there is an additional stream of literature on taxi drivers labor supply choices.[3] More recently, Buchholz et al. (2016) proposed a semiparametric model to estimate the dynamic discrete choices of NYC taxicab drivers and to understand the dynamic labor supply in the taxi industry.

Our study differs from all these existing studies in its focus on the decision making behavior of taxi drivers. It does so using a rich data set consisting of not only fine-grained GPS trip records and taxi drivers' incomes per trip, but also *the associated taxi occupancy data* (i.e., whether a taxi was occupied with a passenger or was vacant). This capacity to use data where occupancy of the taxi is known is a distinctive feature of our data set and sets this work apart from all the prior

[1] `http://www.nyc.gov/html/tlc/downloads/pdf/2014_taxicab_fact_book.pdf`

[2] `http://life.china.com.cn/2015-12/28/content_37408261.htm`

[3] These studies have mainly focused on the relationship between taxi drivers' daily wage targets and taxi labor supply. For example, Camerer et al. (1997), Farber (2014) have studied taxi drivers' behavior during rainy days. They found that taxi drivers seem to not behave in a fully rational way by following the demand during bad-weather days. The drivers tend to quit work early on rainy days once they are satisfied with their earnings (rather than maximizing their earnings). Crawford and Meng (2011), Farber (2005, 2008) have studied the labor-leisure tradeoff for drivers.

work which has attempted to study driver behavior (e.g., Buchholz (2015), Buchholz et al. (2016), Ferreira et al. (2013), Salz et al. (2015), Wang et al. (2014), Zheng et al. (2015)). In particular, our data enables us to learn the real-time spatial and temporal contexts while a taxi is empty and is searching for passengers. It reveals the entire demand-searching process of a driver, the information the driver has been exposed prior to and during the search process, as well as potential interactions among drivers (e.g., a driver may see another driver pick up or drop off a passenger on the road, or two drivers may see each other pass by). Such information can provide important market demand signals to drivers when they try to make a decision where to drive when searching for passengers. But this information was unobserved in all the previous studies. In other words, *in this study we observe not only the matches made between drivers and passengers in the taxi market, but also the complete search trajectories leading to these matches.* Hence, the specific decision we focus on pertains to actions drivers take to find new passengers after they have dropped off their current passengers. We study the role of information derivable from the full GPS trace data (e.g., where passengers are dropped off, where passengers are picked up, longitudinal taxicab travel history with fine-grained time stamps) observable by or made available to drivers to enable them to learn the distribution of demand for their services over space and time.

More specifically, we are interested in recovering the overall distribution of taxi demand in the city by analyzing individual driver-level behavior trace data. We aim to examine how taxi drivers learn from different types of contextual information (e.g., popularity of a location, time of day) and social information (e.g., nearby taxi drivers' pick-ups or drop-offs), by answering the following three research questions:

- How do taxi drivers infer the distribution of demand in the city based on the different information that they are exposed to at different locations at different time periods?
- How do different drivers respond to such information differently and how is their response associated with their economic performance?
- How can we leverage the knowledge we obtain from the taxi traces to improve decision making for both individual drivers and policy makers?

To address these questions, we propose and estimate a structural model of heterogeneous learning at the individual-driver level. We validate our study using a combination of three large, unique data sets containing complete information on 10.6 million individual trip records from 11,196 taxi drivers in a large Asian city in September 2009: (1) the taxi's GPS trajectory data (e.g., real-time geographic coordinates and time stamps at the minute level); (2) the taxi's trip-records data (e.g., trip distance, geographic coordinates of pick-up and drop-off location, and amount paid for the trip); and (3) geo-spatial map data (e.g., type and density of points of interest). Note the combination of these three data sets allows us to observe taxi drivers' behaviors not only when their cars have passengers, but, more importantly, when their cars are empty i.e., when they looking for passengers. In addition, another unique advantage of our setting is that our data contain information from all the taxis playing in the city from multiple taxi companies (rather than from a single taxi company). Hence, the combination of the above three data sets enables us to recover the distribution of the overall taxi demand that is served in the city.

The summary list of findings from our empirical analyses are as follows. *First*, the results indicate strong heterogeneity in city demand across both spatial and temporal dimensions. *Second*, different information signals from various social contexts have different values for the drivers in learning the city demand. On average, observing other drivers' pick-ups can directly reveal demand information of the current location in the current time period. This information is most valuable for an individual driver to learn demand. In contrast, observing other drivers' drop-offs and drive-bys may not be as valuable at individual level. This is mainly because drop-off and drive-by signals at the individual level cannot directly reveal demand for the current location in the current period. Instead, they are indirect demand signals, and only reveal demand for the current location in a future time period (drop-off) or demand for a different location in a previous time period (drive-by). To be able to learn from the drop-off and drive-by signals, drivers need to draw knowledge from the distribution of the demand flows across spatial and temporal dimensions. Hence, these two types of signals are relatively more complex information for individual driver to learn compared to the pick-up signals. *Third*, our findings indicate significant heterogeneity across taxi drivers with regard to their learning behavior. The degree of heterogeneity varies among the three signals. Interestingly, we find that straightforward information, such as the pick-up signal, is not as valuable for drivers in their efforts to earn a high income. Instead, drivers with a higher income and from larger companies benefit largely from their ability to learn from more complex signals such as drop-offs. These drivers are able to better interpret not only demand information directly observable in their own local markets (i.e., current location and current time period), but also aggregate information on demand flows across markets (i.e., demand flows across locations and time). *Fourth*, our policy-simulation results show that by aggregating the information extracted from the offline behavioral trace on a large scale, we can significantly improve the quality of individual drivers' decision-making. Interestingly, we find that information that is noisy at the individual level can become most valuable after we aggregate it across various spatial and temporal dimensions. We also find the value of information does not increase monotonically with the scale and frequency of information sharing, and the marginal value of aggregating large-scale information varies among different types of information. *Finally*, our study has important welfare indication that efficient information sharing leads to an income increase among all drivers, instead of an income shift among different types of drivers. Our work allows us to not only explain driver decision making behavior using these detailed behavioral traces, but also prescribe information sharing strategy for the firm in order to improve the overall market efficiency.

The key contributions in this paper can be summarized as follows: (1) Our study demonstrates the value of extracting behavior patterns from large-scale, fine-grained physical trace data to understand and improve human decision making. In particular, by collecting and analyzing this new source of information, we are able to extract knowledge that is often unavailable to individuals or organizations in the conventional setting. (2) We develop a heterogeneous Bayesian learning framework to examine drivers' learning process for city demand based on various information to which they are exposed. In this model, we distinguish among three different information signals extracted from the GPS trace. One methodological innovation of this framework is that we model these three information signals differently in accordance with their contexts. In our model, the learning process is contingent on each driver's own experience, observed peer behavior, and accumulated knowledge of how to interpret different signals in different ways. This model allows us to jointly identify the heterogeneity in individual learning ability as well as in the value of different types of information in real-time decision making. (3) To the best of our knowledge, this research is among the first to study taxi demand and drivers' learning behaviors based on utility theory from economics. Such an approach allows us to build a linkage between individual behavior and economic outcome from a more explanatory perspective. We aim to provide insights on how and why drivers behave in certain ways, and how observed and unobserved individual characteristics can explain their behaviors. (4) Our unique data set enables us to study driver behavior from not only the trip trajectories when taxis are occupied with passengers, but also drivers' full search trajectories when their taxis are unoccupied and on the way searching for passengers. This feature distinguishes our study from all the previous work. The combination of trip trajectory and driver-search trajectory data provide us with a holistic view of drivers' decision-making processes to reveal their preferences. (5) On a broader note, this work demonstrates the potential to combine large-scale temporal and spatial data mining together with econometric structural models and Bayesian statistics to understand human behavior. With the growing ubiquity of mobile and sensor technologies adopted at the individual level, more and more human behavioral information is digitized and associated with location and time stamps. We note that our work appears to have relevance to the decision making contexts that drivers in ride sharing platforms face as well though this is not a focus of our paper. Informal interviews with Uber drivers by the authors indicate that Uber drivers also exhibit behavior similar to taxi drivers in having to decide where to go to get their cars occupied. In future work, we propose to build on foundational work in this paper to study decision making in other offline settings.

The remainder of this paper is organized as follows. Section 2 briefly discusses previous studies related to this paper. Section 3 describes our unique data sets and provides preliminary model-free evidence. Section 4 develops a heterogeneous Bayesian learning model to capture the dynamics of drivers' decision-making behavior. In section 5 and section 6, we present our estimation methods and empirical results. Based on the estimates of our structural model, we ran three policy-simulation experiments, and we present the results in section 7. Section 8 concludes with discussions of the major contributions of this research, as well as an outline of directions for future studies.

2. Literature Review

Our study draws from the following two major streams of literature:

First, our study is related to literature on computational urban analytics. In particular, the availability of real-time GPS trace data has attracted many researchers from computer science or transportation fields to drivers' behavior analytics using machine-learning techniques. Existing studies mainly contain two categories: exploratory and predictive analyses. The first category of studies tries to explore behavior patterns of taxi drivers (e.g., Liu et al. (2010a,b), Liao et al. (2006), Balafoutas et al. (2013)). For example, Liu et al. (2010a) explored taxi trace data on driver behaviors, including route-choice behavior and spatial-selection behavior. Liu et al. (2010b) proposed a mobility-based clustering method to identify hot spots of moving vehicles in an urban area. The second category of studies focuses on predictive analysis based on the historical behavior of the drivers (Liu et al. (2013a), Hunter et al. (2009), Ge et al. (2010), Yuan et al. (2011)). For example, Liu et al. (2013a) proposed an inverse reinforcement learning framework to study drivers' objective functions (i.e., minimize driving distance, minimize idle time, or maximize number of passengers) when seeking next passengers. Ge et al. (2010) developed a mobile recommender system that has the ability to recommend a sequence of pick-up points for taxi drivers or a sequence of potential parking positions. Yuan et al. (2011) proposed a system for computing the shortest-time driving routes using traffic information and driver behavior. However, most previous studies focused mainly on exploring how drivers behave or predicting what future driving routes should be, whereas few studies have looked at why drivers behave in certain way and why they behave differently. To answer these questions, we need to look into the incentives that drive users' behavior. In this paper, we aim to bridge this gap.

Second, our paper is related to the social and economic perspective of the taxi (or more generally speaking, vehicle-for-hire) market (e.g., Camerer et al. (1997), Farber (2005, 2008, 2014), Crawford and Meng (2011), Greenwood and Wattal (2015), Wu et al. (2015), Hall et al. (2015), Zheng et al. (2015). More specifically, Camerer et al. (1997) analyzed the relationship between the hours supplied and the changes in taxi drivers' wages, developed a behavioral economic theory and explanation of this relationship. Farber (2005, 2008, 2014) and Crawford and Meng (2011) have studied the labor-leisure tradeoff for drivers. These studies have mainly focused on the relationship between taxi drivers' daily wage targets and taxi labor supply. Wu et al. (2015) showed that the taxi-hailing mobile apps increase taxi drivers' productivity and reduce the gap between high- and low-skilled drivers. Hall et al. (2015) illustrated the economic value of Uber's surge-pricing algorithm. Greenwood and Wattal (2015) studied this topic from the social perspective by looking into the effects of the entry of ride-sharing services on alcohol-related motor vehicle homicides. Zheng et al. (2015) identified that the intensive promotion in transportation network apps can attract taxi drivers in both the short and long run. Our paper distinguishes itself from these existing studies in that we aim to understand from a micro perspective how individual drivers learn to use various information signals to infer taxi demand in the city and to make driving decisions in real time. We achieve this by analyzing large-scale and granular-level taxi GPS traces.

Two recent studies that are highly related to our paper are Salz et al. (2015) and Buchholz (2015). Both work focused on the economic demand and individual-level driver decision making problem in the taxicab industry. By analyzing the NYC yellow medallion taxi data, they attempted to study the matches made between drivers and passengers revealed from the taxis' pick-up and drop-off data to explain the market inefficiency under regulation. Salz et al. (2015) studied the effect of regulations on aggregate city-level taxi service and demand. Buchholz (2015) studied the dynamic equilibrium effects of regulations on spatial search frictions and welfare. Another related work by Buchholz et al. (2016) proposed a semiparametric model to estimate the dynamic discrete choice of NYC taxicab drivers and to understand the dynamic labor supply in the taxi industry. Our paper distinguishes itself from these three papers in that we focus on individual-level driver decision process and study the value of real-time demand information signals to different drivers when they search for taxi demand. We aim to understand and reduce potential market inefficiency by accounting for the heterogeneity among individual drivers. Moreover, in our study we observe the taxi occupancy data, including not only the matches made between drivers and passengers, but also the drivers' complete search trajectory when the taxis are unoccupied. Our unique data set provides us a holistic view of drivers' full decision-making processes.

Lastly, our paper is also related to literature on consumer Bayesian learning models, which have been widely applied to analyze consumers' choices under uncertainty in the fields of marketing, IS, and economics. One of the most influential papers is Erdem and Keane (1996), which proposed a structural model to estimate learning signals from both purchase experience and advertisement. Since Erdem and Keane, Bayesian learning models have been widely used in various fields, including health technology adoption (Hao et al. (2014)), crowdsourcing (Huang et al. (2014)), and wireless-service adoption (Iyengar et al. (2007)). This general framework contains different types of learning models (Ching et al. (2013)) depending on the assumptions about the consumer behavior: (1) Myopic versus forward-looking manners. “Myopic” means the consumers choose the product with the highest expected current utility. Some recent studies assume people behave in a myopic manner without any active search (Huang et al. (2014), Narayanan and Manchanda (2009)). Others make a further step by assuming individuals are “forward-looking” and make choices based on the total expected utility over a time horizon including both the current period and the future (Erdem and Keane (1996), Ackerberg (2003)). (2) Homogeneity versus heterogeneity. Some papers assume individuals learn in the same way and have the same preferences (Erdem and Keane (1996), Hao et al. (2014)), whereas others allow individuals to have heterogeneous preferences and to learn differently even when receiving the same signals (Huang et al. (2014), Narayanan and Manchanda (2009)).

3. Data

We use a combination of three large, unique data sets containing 10.6 million individual trip records from 11,196 taxi drivers in a large Asian city in September 2009. This section describes our data and the detailed process about how we transform the raw data and extract our model variables.

3.1. Background

The large Asian city in our data had a population of approximate 10 million people in 2009 and the urban population density was around 14,000 per square mile. Multiple taxi companies ran businesses within the city. The city policy regulated that taxis with urban tags could only drive within the downtown areas, whereas the taxis with suburban tags could only drive in rural areas (outside-downtown area). When a taxi was empty, to figure out when and where passengers might be waiting for a taxi in real time, a taxi driver would often make driving decisions based on his/her own experiences (e.g., passenger pick-ups or drop-offs) and observed peer behaviors (e.g., other drivers’ pick-ups, drop-offs or drive-bys) on the road. More experienced drivers, who have often been exposed to such demand signals over a longer period, might be able to more precisely pin down the locations with a higher probability of picking up the next passengers.[4]

3.2. Data Description

We conduct the empirical analysis on a combination of three large data sets: (1) taxi drivers’ GPS-coordinates tracking data, (2) taxi-trip-records data, and (3) geo-spatial map data. Note that our full data set covers all existing companies in the focal city, which allows us to infer the overall city

[4] Note that although taxi-hailing mobile apps are quite popular today, people rarely used them in 2009. Thus, they are not the focus of this paper. However, our methods and analyses have the potential to be generalized to the more recent taxi market as well. For example, our analyses have the potential to improve the taxi-hailing services today in recommending better personalized taxi-demand information to individual drivers.

demand from the individual taxi trace. Such coverage is one advantage of our cross-company data, because no single company data set can observe all the information signals each driver receives to recover the true spatial and temporal demand.[5]

Taxi drivers' GPS-coordinates tracking data: Each taxi GPS-tracking record includes taxi ID, real-time geographic coordinate information (i.e., longitude and latitude), recorded time, taxi company ID, and taxi type ID. Due to city policy, taxis are divided into three types: *urban* taxis that can only drive within the downtown area, *suburban* taxis that can only drive outside the downtown area; and *other* taxis that can drive anywhere in the city. The GPS tracking data were recorded approximately every 50 seconds.

Taxi-trip-records data: Each trip record includes taxi ID, geographic and temporal information of starting and ending points, trip amounts (i.e., total money paid by the passengers) and total distance, taxi company ID, and taxi type indicator. Combining these data with the GPS tracking data, we have full GPS trajectories of a total of 10.6 million trip records from 11,196 taxi drivers in September 2009.

Geo-spatial map data: This data set consists of two parts: POIs (point of interest) and road intersections. Each POI has its geographic location and name, based on which POI can be classified into different categories (which we will discuss in the next subsection); each road intersection has its geographic coordinates.

We visualize our data set with four sample drivers' trajectories on September 1, 2009 (shown in Figure 1).

Note the combination of these three data sets allows us to observe the full taxi trajectories not only when the cars have passengers, but also when the cars are empty (e.g., when looking for passengers). This is an important feature of our data over most other publicly available data sets (e.g., the NYC TLC open data: `http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml`) that contain only the trip-records data (i.e., when the cars have passengers).

3.3. Variable Extraction

This subsection discusses how we code important variables based on the data sets for our model.

(a)Division of City Plane

[5] One potential limitation of our data is that we do not observe the potential "unserved" demand - if a customer wanted to hail a taxi but did not find one, we would not observe such demand in our data. We also do not observe the actual waiting time of passengers. Hence, we do not know exactly when and where a customer's demand first initiated. Such data limitation is common across all the existing studies on the taxi market (e.g., Salz et al. (2015) and Buchholz (2015)). However, we are able to recover all the "served" demand. In other words, as long as customers did not switch to alternative transportation mode (e.g., walk, bus), we would be able to capture their demand at a certain time (i.e., Customers who wait longer will be captured by demand at a slightly later time). Therefore, albeit this potential limitation, our data give us a close approximation of the overall taxi demand in the city.

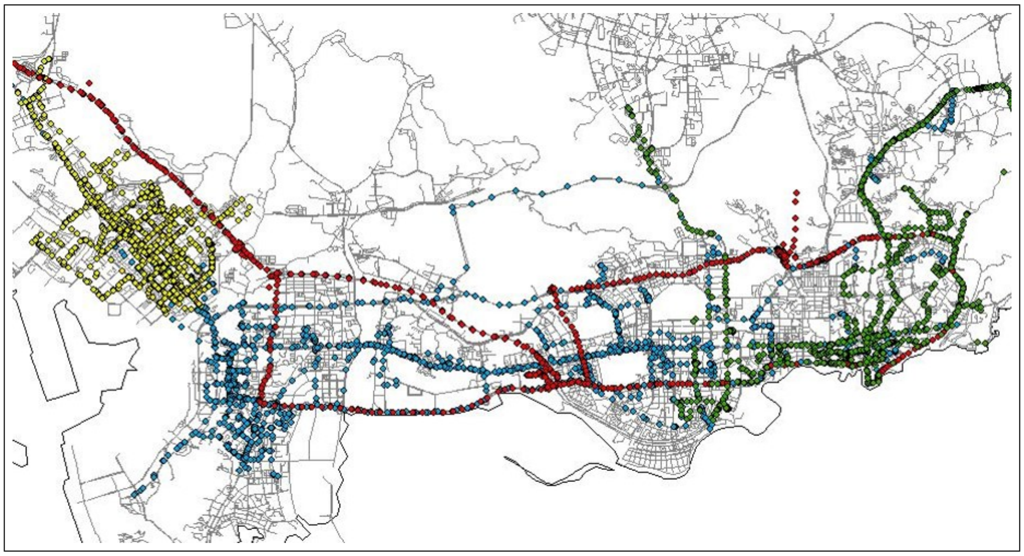


Figure 1 Data Visualization of Driving Trace Plot with the City Map

Figure 1 (The gray lines are streets of the downtown area in the big Asian city. Each color represents a sample driver.)

We use Voronoi diagrams (Aurenhammer (1991)) to partition the city plane into grids based on the road intersections. In particular, each road intersection is assigned to a unique corresponding location grid. Any point within the grid is closer to the corresponding intersection than to the other intersections (Okabe et al. (2009)). Thus, the number of road intersections is exactly the same as the number of location grids in the data set. We assume the drivers make decisions and update their knowledge of demand at the level of a location-grid unit. The road intersection may distribute sparsely in some rural areas. To keep the sizes of location grids similar, in this study, we focus only on the downtown area of the city (which covers approximately 70% of the taxi demand). This approach results in a total number of 87 road intersections (87 location grids).

(b) Extraction of Location Type, Time-of-Day, and Static Location Features

We classify the above 87 location grids into six location types according to POIs within each location grid. A POI is a specific useful or interesting location for geographic identification. First, we conduct a text analysis to classify all 25,317 POIs into different location types based on the keywords in the POI names, using a supervised-learning method.[6] Our algorithm identifies six major types of locations: *shopping area*, *entertainment area*, *office area*, *residential area*, *transportation hub*, and *others*.[7] However, a location grid often contains a mixture set of different types of POIs.

[6] We also tried unsupervised learning in this case to reduce the manual effects in constructing the training data based on domain knowledge. Some examples of unsupervised learning include: topic modeling (Blei et al. (2003)) and DBSCAN clustering (Ester et al. (1996)). However, the results were not satisfying, because the names are short and diverse.

[7] Some POIs provide general utilities (e.g., parking lots, gas stations) to residents and do not belong to any of the first five types. Thus, we classify them into a separate type called “others”.

For example, a location grid can have a large number of both shopping and entertainment POIs. Therefore, to capture the distribution of different types of POIs within the same location grid, we assign each location grid a weight vector of the corresponding six location types. The weights are the corresponding probability densities of the different types of POIs within the location grid. For computational tractability, we define each location grid as belonging to a dominant location type that has the highest weight of POI density in that location grid.

Moreover, to control for the temporal effect, for each location, we consider four time-of-day periods: midnight (12am-6am), morning (6am-12pm), afternoon (12pm-6pm), and evening (6pm-12am). Thus, our model is able to estimate city demand for six types of locations and over four different time-of-day periods.

Based on the above definitions, we extract two static features or variables from our static geographic data set to control for the popularity of a location. The first variable is the POI density. This captures the total number of POIs within a location grid. The second variable is the percentage of all location grids in the city that belong to the same dominant location type as the current location grid. This captures the overall popularity of a location type in the city.

(c)Extraction of Information Signals

One advantage of our data set is that, based on all the taxi trace information, we are able to recover the offline demand signals a driver is exposed to while driving. Such offline demand information allows us to better understand the overall decision process of a driver at a much finer level (i.e., minute or second level). Note this granular offline information was usually unobserved in the conventional setting for decision analytics. For example, without the taxi GPS trajectory data, backtracking how many other taxi cars drove by or stopped to pick up or drop off a passenger while a taxi driver was driving, and at what time and location, would be difficult. Understanding whether and how a taxi driver might use such observed information on the road for real-time decision making would also have been difficult.

We use the GPS trajectory data to extract all the potential activities of other peer drivers that could have been observed by a driver on his/her driving path. In particular, we focus on three types of peer activities as real-time demand information signals: pick-up, drop-off, and drive-by. These three information signals are associated with tasks a driver is engaged in while providing service to passengers. We assume that when a driver observes any of these three activities in other peer taxi drivers in the same location at the same time, he/she can gain some additional (but potentially noisy) knowledge about the demand in the local area during that time period. We aim to extract this information from our data and to model the value of these real-time demand information signals in drivers' decision-making process.

More specifically, we extract pick-up and drop-off signals from the taxi-trip-records data using the starting and ending time and locations. We extract drive-by signals from both the trip-records data and the GPS-tracking data. Specifically, first, we extract a driver's trajectory from the GPS tracking data to summarize what location grids the driver drives by during any 10-minute bins. Note that in our main estimation, we use a 10-minute time slot as the unit of analysis for driver learning, which is why we extract all the information at the 10-minute window. We will discuss more details on this definition in the next section. For robustness check, we have tested other definitions of the time bin, such as 30 or 60 minutes. We find the results are qualitatively consistent. Then, according to the definition of signals, a driver would only receive a signal if he/she passes a given location where the number of corresponding activities (pick-up, drop-off, or drive-by) for any taxi in that location is nonzero in the same time period (i.e., within the same 10-minute bin). We provide more details on how we define and incorporate these three signals into modeling drivers' decision process in the next section.

(d)Extraction of Choice Decisions

We assume taxi drivers make driving decisions if and only if the taxi is empty. In other words, when a taxi is empty, the driver needs to choose between staying and leaving the current grid to look for potential passengers. We extract drivers' decisions by combining the two real-time data sets. First, we need to detect when the taxi is empty. If the GPS trace shows a driver is driving but has no associated trip record for the corresponding time, we are able to detect that the state of the taxi is empty. Then, to infer the driver's decisions we look into the GPS trace data. If within a given 10-minute time slot, the driver only drives within the same location grid, we define the decision as *Stay*; otherwise, we define the decision as *Leave*.

(e)Extraction of Individual Demographics

To capture individual heterogeneity, we consider two individual-specific features: company indicator (i.e., whether the company is larger or not) and income level. Our data cover 109 taxi companies in the focal city. Some companies have significantly more taxis than other companies. Thus, we divide the companies into two categories: large companies (with more than 200 taxis) and small companies (otherwise). The second feature is drivers' hourly income level. We use the hourly income instead of daily income to control for the length of working time (e.g., a high daily income may not come from efficient decision making but simply long working hours).

For a better understanding of variables in our setting, we present the definitions and statistics summary of all variables in Table 1.

3.4. Model Free Evidence

Before modeling the detailed decisions, we would like to explore our data to develop intuition about individuals' behavior. Figure 2 shows the distributions of individual drivers' daily number of trips

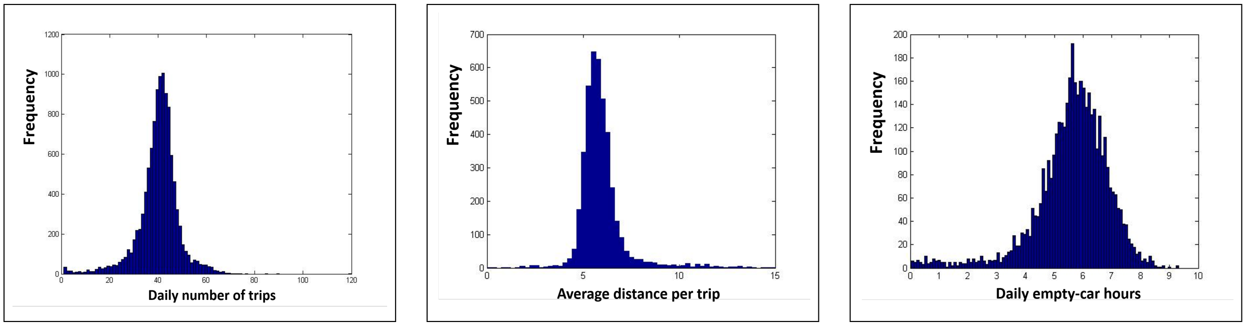
Table 1 Variable Definition and Statistics Summary

Variable	Definition	Mean	Std.err	Min	Max
Stay	Staying in the same grid within a 10-min slot with an empty taxi	0.0017	0.0017	0	1
Leave	Passing more than one grid within a 10-min slot with an empty taxi	0.9983	0.0017	0	1
d_{PU}	Receiving a pick-up signal	0.4099	0.2419	0	1
d_{DO}	Receiving a drop-off signal	0.4377	0.2461	0	1
d_{DB}	Receiving a drive-by signal	0.6956	0.2114	0	1
$POIDensity$	Total number of POIs within a location grid	159.4828	324.6050	2	2,349
% of intersections	The percentage of location grids that belong to a location type	16.6667	6.638	9.0224	25.4177
$Income$	Individual's hourly income	60.4185	24.2051	8.8488	1109.48
$Company$	Whether the driver is from a large company (with more than 200 taxis)	0.4906	0.4999	0	1

(Figure 2a), average distance per trip (Figure 2b), and average daily empty-car hours (Figure 2c). Each trip represents a taxi pick-up. Distance per trip is the driving distance when the taxi is full. Empty-car hours are the amount of time the taxi is empty and the driver is seeking the next passengers. The three plots suggest significant heterogeneity in taxi drivers' behavior. Figure 3 shows individuals' daily number of trips over time (for illustration, we present five randomly sampled drivers in the plot). On average, a driver's daily number of trips increases but the rate of increase differs between individuals. Generally, our data indicate two types of drivers: (i) more experienced drivers (shown as solid lines) who behave relatively stable over time with only a small increase in the number of daily trips, and (ii) new drivers (shown as dashed line) who significantly improve their performance over time. This plot suggests that drivers become more knowledgeable about the taxi demand through learning, but the rate of learning is heterogeneous among individual drivers. To summarize, Figure 3 shows that for each driver, on average, learning behavior seems to exist over time. More importantly, significant heterogeneity exists in drivers' learning behavior. In the next section, we propose a heterogeneous structural model to explain what factors may drive these observations.

4. Model

Following Erdem and Keane (1996), we develop a Bayesian learning framework to model how taxi drivers learn the taxi demand in the city. Such a structural modeling mechanism helps us



(a) Daily Number of Trips (b) Average Distance per Trip (c) Daily Empty-Car Hours

Figure 2 Distributions of Drivers' Behavior

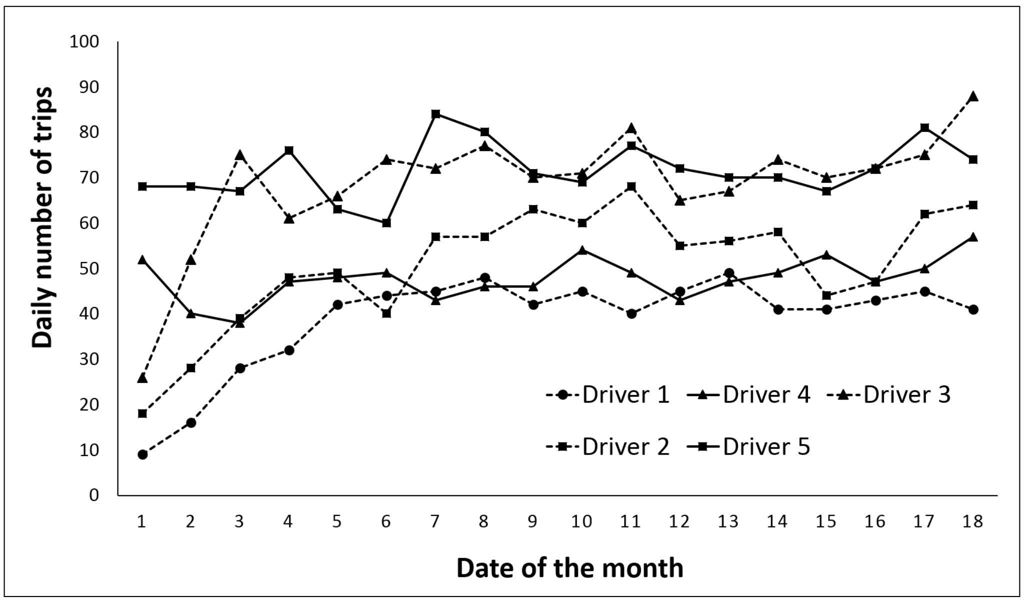


Figure 3 Individual Daily Numbers of Trips over Time

explicitly model individual decision making process through the utility function. In addition, our model explains how drivers' uncertainty about the taxi demand is resolved via three different information signals with a Bayesian updating process. We start by first explaining the individual utility function.

4.1. Utility Function

The value of a location (grid) to a taxi driver is its potential taxi demand from the passengers. That is, the larger the probability that a driver can pick up the next passenger in a location grid, the higher the value of that location grid to that driver. Thus, we model the utility a driver gains from a location as a function of demand. However, demand is an abstract concept for drivers and cannot be fully observed. On the one hand, certain observed static location features can reflect the taxi demand. For example, an area with more buildings may indicate a higher population density, which leads to a higher taxi demand. On the other hand, other potential factors exist that may not be directly observable to the drivers at that moment and may only be revealed over time. For instance, some unobserved demand factors might be revealed through drivers' past pick-up or drop-off experiences which can help reduce the uncertainty in drivers' beliefs about the true demand beyond the observed location features. Therefore, we model the utility to be a combination of observed demand (as captured by the observed features) and unobserved demand (learned by the drivers over time). More formally, we describe the utility function as follows:

Suppose I individual drivers are in the market. Each driver $i(i=1,2,,I)$ updates his/her knowledge of demand, and then decides whether to stay in the current location or leave for another location at a given time. As we discuss in the data section, the taxi demand can vary across locations and over time. Thus, for each alternative (a location at a given time period), we use $j(j=1,,J)$ to represent a tuple with spatial and temporal elements, $j=(l,\tau)$, where l denotes location grid and τ denotes the time of day. During each time period t, the driver makes choices based on the overall utility of the location at the current time of day. The utility is defined as a linear function of the demand at each j. In general, the utility (as shown in eq. (1)) is a function of the mean demand and a random error term ε_{ijt}, which captures any idiosyncratic shock during the decision process. We assume ε_{ijt} to be i.i.d. and to follow type I extreme value distribution:

$$\begin{aligned}\tilde{U}_{ijt} &= f(Demand_{ijt}) + \varepsilon_{ijt} \\ &= f(ObservedDemand_{jt} + UnobservedDemand_{ijt}) + \varepsilon_{ijt} \\ &= \beta X_j + \delta \tilde{Q}_{ijt} + \varepsilon_{ijt}.\end{aligned} \tag{1}$$

As mentioned above, we model the overall demand as a combination of two components: observed ($ObservedDemand_{jt}$) and unobserved ($UnobservedDemand_{ijt}$). The observed demand consists of several static spatial features of the location grid (X_j). In this study, we consider two features we introduced in section 3.3 (b): (1) POI (points of interest) density and (2) percentage of location grids in the city that belong to the same location type. The coefficient vector β captures drivers' preferences towards these observed features. The unobserved demand is denoted as $\tilde{Q}_{ijt}$, which varies among individuals because different drivers perceive different levels of uncertainty in demand depending on the information to which they are exposed. δ captures drivers' preference towards the unobserved demand. Note that we will first discuss the case when drivers have homogeneous preferences (i.e., β and δ are not individual-specific). In subsection 4.3, we will relax this assumption and allow each driver to have an individual-specific preference factor, β_i and δ_i. We assume the driver makes decisions based on the expected utility value. Thus, this expected utility is

$$U_{ijt} = E(\tilde{U}_{ijt}) = \beta X_j + \delta E(\tilde{Q}_{ijt}) + \varepsilon_{ijt}. \tag{2}$$

4.2. Learning Process

When driving around the city, the drivers may be able to update their expectation of the unobserved demand through their own passenger-pick-up experiences or by observing peer behaviors on the road, such as other taxis' pick-ups, drop-offs, and drive-bys. These types of information can help drivers reduce the uncertainty about their expectations about the unobserved demand. To model this learning process, we follow a standard model of Bayesian learning by assuming drivers update their beliefs in a Bayesian fashion. For tractability, we divide a day into 144 time slots and assume that drivers will update their knowledge of the unobserved demand every 10 minutes.[8] As we discussed in the previous section, we consider three different information signals to which a driver is potentially exposed in an offline setting.

(a)Pick-up Signals

It is intuitive that if a location has more pick-ups within a given time period, it is more likely to indicate a higher local demand. Pick-ups in a given location are either pickups generated by an individual driver or by other drivers. Thus, if a driver passes a location l with one or more pick-ups (either self-generated or observed from activity of other drivers) during the given 10-minute slot t, we assume he/she receives a pick-up signal at location l and corresponding time-of-day τ (combined to $j = (l, \tau)$), and will update his/her knowledge about the unobserved demand at j. Note τ is the time-of-day period that contains the given 10-minute unit of time for learning updates.

However, each driver may not precisely evaluate the messages from pick-up signals. For example, it is possible that the driver is not aware of all the pick-ups the other taxi drivers made, or some unexpected random shocks might affect the overall number of pick-ups. Thus, similar to previous studies (Erdem and Keane (1996), Huang et al. (2014)), we assume the content of the information from pick-up signals (i.e.,S_Pick_{ijt}) follows a normal distribution around the true unobserved demand:

$$S\_Pick_{ijt} \sim N(Q_j, \sigma^2_{Pick}), \tag{3}$$

where σ^2_{Pick} is the variance of the content of the pick-up information signal, which indicates the precision of the information contained in the pick-up signals. A greater value of σ^2_{Pick} suggests a less precise signal.

(b)Drop-off Signals

A previous drop-off can lead to a potential future pick-up in the same location. For example, a consumer may go to a shopping mall at 7pm and spend around three hours in it. Thus, the drop-off at 7pm may lead to potential future demand at 10pm. To model such complex additional

[8] Our data show that the average driving speed is around 30km/h and the approximate circumference of a location grid is around 4.8km. Thus, driving around an area takes approximately 10 minutes. Therefore, we choose 10 minutes as our unit of analysis for knowledge update and decision making.

information, we consider the drop-off signal in drivers' learning process. Specifically, suppose that a driver passes a location l where one or more drop-offs occurred during the given 10-minute slot t (say its corresponding time-of-day is τ_0). The driver will update his knowledge of future demand in j,where $j = (l, \tau)$ is a combination of the same location and a future time slot. Here, $\tau = \tau_0 + \Delta$, where Δ is the time gap between the current drop-off and the future pick-up. We also assume the information content in the drop-off signal, similar to the pick-up signal, follows a normal distribution with variance σ^2_{Drop}, which indicates the precision of the drop-off information:

$$S\_Drop_{ijt} \sim N(Q_j, \sigma^2_{Drop}). \tag{4}$$

Note that in the real world, the taxi drivers may not know exactly how each current drop-off will transform into a future pick-up. However, we assume a driver would have some ex-ante knowledge of the probability distribution of Δ. To model the time gap, we use historical data to recover the empirical distribution of the future pick-up probability conditional on the current drop-off. We assume this information is common knowledge for all drivers.

(c)Drive-by Signals

A drive-by occupied (i.e., with a passenger) taxi in a location may not directly reflect the current location's demand. However, it may give us some hints about the demand in the locations from where the taxi possibly came. Thus, if a driver knows where and when the drive-by occupied taxi might originate, he/she can update his/her knowledge of the unobserved demand in that original location and time.

To model the drive-by signal, we first recover the set of all possible starting location and time combinations (j) for each drive-by occupied taxi. We apply a similar approach as described above for the drop-off signals: to recover the set of all possible starting points, we use the historic data to estimate the empirical joint distribution of the original pick-up location and time conditional on each drive-by signal. Hence, if at time τ_0 and location l_0 (which gives $j_0 = (l_0, \tau_0)$), a driver observes a drive-by signal, the driver will update his/her knowledge of the demand in j, where $j = (l, \tau)$ is a combination of the original pick-up location and time. That is, $l = l_0 - \Delta l, \tau = \tau_0 - \Delta\tau$, where Δl and $\Delta\tau$ represent the location and time gaps between the current drive-by and the original upstream pick-up. Note by deriving the upstream pick-up demand from all the drive-by signals, a unique advantage arises that allows us to also capture the upstream pick-ups derived from special drive-by signals at the points where the passenger exits the taxi. Such special drive-by signals are essentially the drop-off signals. Therefore, while learning from the drive-by signals, we are able to augment the learning from the drop-off signals by inferring the original upstream pick-ups, in addition to inferring the potential future downstream pick-ups from the drop-off signals directly (as discussed in (b)).

Similarly, we assume this information is common knowledge among all drivers. Note this empirical distribution is able to account for the potential effect from the location popularity. In other words, if a location is of higher popularity (e.g., a large shopping mall), it is likely to have more pick-ups, which lead to a larger probability of being potential starting point for the drive-bys. Again, similar to the previous two signals, the information content in each drive-by signal follows a normal distribution with variance σ^2_{Drive}, which indicates the precision of the drive-by information:

$$S\_Drive_{ijt} \sim N(Q_j, \sigma^2_{Drive}). \tag{5}$$

To illustrate the three signals better, we summarize them in Figure 4. Pick-up signals help drivers update their beliefs about demand at the same locations and same time periods. Drop-off signals help drivers update their knowledge of future demand $(t + \Delta t)$ at the same location. Drive-by signals provide information about upstream demand, and the drivers need to infer both the temporal $(t - \Delta t)$ and spatial $(l - \Delta l)$ information about starting points.

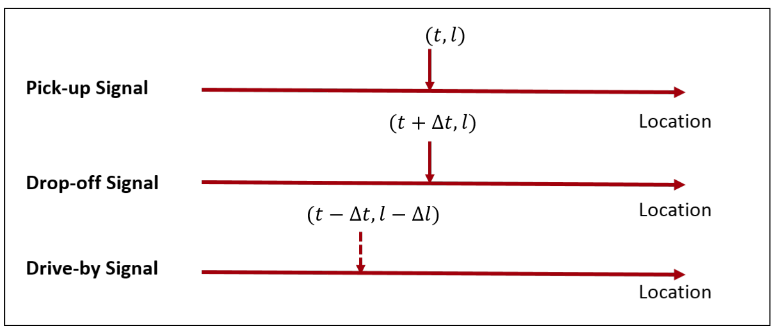


Figure 4 Summary of Three Signals.

(d)Updating Procedure

At t_0, before receiving any information, the drivers start with some prior beliefs about the true unobserved demand, Q_j, which is assumed to be normally distributed with mean Q_0 and variance σ^2_0. Over time, the drivers receive the surrounding signals to update their beliefs about this distribution. By using Bayes rule (DeGroot (2005)), drivers will update their posterior beliefs conditional on the prior belief and signals. Because prior belief at time t_0 and all signals are assumed to be normally distributed, the posterior beliefs at any time period also follow a normal distribution. The posterior belief is given by

$$\tilde{Q}_{ijt} \sim N(Q_{ijt}, \sigma^2_{ijt}), \tag{6}$$

where

$$Q_{ijt} = \left[\frac{Q_{ij,t-1}}{\sigma^2_{ij,t-1}} + \frac{d_{PU,ijt} S\_Pick_{ijt}}{\sigma^2_{Pick}} + \frac{d_{DO,ijt} S\_Drop_{ijt}}{\sigma^2_{Drop}} + \frac{d_{DB,ijt} S\_Drive_{ijt}}{\sigma^2_{Drive}} \right] \cdot \sigma^2_{ijt} \tag{7}$$

and

$$\sigma_{ijt}^2 = \left[\frac{1}{\sigma_{ij,t-1}^2} + \frac{d_{PU,ijt}}{\sigma_{Pick}^2} + \frac{d_{DO,ijt}}{\sigma_{Drop}^2} + \frac{d_{DB,ijt}}{\sigma_{Drive}^2} \right]^{-1}, \tag{8}$$

where $d_{PU,ijt}, d_{DO,ijt}$, and $d_{DB,ijt}$ are the indicators of whether driver i receives a pick-up, drop-off, or drive-by signal about j at time t. As eq. (7) and eq. (8) indicate, the variance of the perceived demand around the true demand declines as drivers receive more signals over time, and finally, the perceived demand will converge to the true value Q_j. Then, given that the belief of unobserved demand in any time period is a normal distribution with mean Q_{ijt} and variance σ_{ijt}^2, the expected utility function in eq. (2) can be rewritten as

$$U_{ijt} = E(\tilde{U}_{ijt}) = \beta X_j + \delta Q_{ijt} + \varepsilon_{ijt}. \tag{9}$$

4.3. Heterogeneous Driver

Drivers with different experiences may have different senses about the taxi demand. In this section, we relax the assumption that individuals are homogeneous in evaluating utility. Instead, we assume individual drivers have heterogeneous preferences towards the observed and unobserved demand. Moreover, drivers also have different learning abilities in interpreting the same demand-related information signals. In other words, the coefficients in eq. (1) have subscript i:

$$\tilde{U}_{ijt} = \beta_i X_j + \delta_i \tilde{Q}_{ijt} + \varepsilon_{ijt}. \tag{10}$$

In addition, the learning process is also heterogeneous, We allow the variances of the information value to be individual specific with a subscript i: $\sigma_{Pick,i}^2, \sigma_{Drop,i}^2, \sigma_{Drive,i}^2$. Thus, we define the heterogeneous parameter vector as $\Theta_i = (\beta_i, \delta_i, log(\sigma_{Pick,i}^2), log(\sigma_{Drop,i}^2), log(\sigma_{Drive,i}^2))$. And the homogeneous parameter vector $\Phi = (\{Q_j\}, Q_0, \sigma_{Q_0}^2)$ is common among all drivers. Following Huang et al. (2014), Narayanan and Manchanda (2009), and Netzer et al. (2008), we specify the individual-specific preference as a function of individual demographic features: $\Theta_i = \Lambda_0 + \Lambda_Z \cdot Z_i + \varepsilon_{\Theta i}$, where Z_i specifies observed individual-specific demographics and $\varepsilon_{\Theta i}$ is the unobserved error term with uninformative prior: $\varepsilon_{\Theta i} \sim N(0, \Sigma_\Theta)$. Λ_0 is a vector of the mean coefficients of the individual-specific preference. Λ_Z is a $nZ \times n\Theta$ matrix where nZ is the dimension of Z_i and $n\Theta$ is the number of individual-specific parameters.

4.4. Individuals' Decision-Making Problem

Individual drivers make decisions based on their expectation of the utility they derive from each alternative (McFadden (1974)). Consistent with the updating process, we assume drivers make choice decisions every 10 minutes, but only when the taxi is empty. In other words, when the drivers are looking for potential passengers (i.e., the taxis are empty), they need to decide whether to stay within the same location grid or drive to other locations. We define the drivers' decision from our data as the following: If a driver stays within the same location grid within a 10-minute slot with an empty taxi, we say the driver is choosing option *Stay*. If a driver with an empty taxi passes more than one grids within the 10-minute slot, we say the driver is choosing option *Leave*. We choose the 10-minute slot as our unit of analysis for driver decision making for the same reason we discussed in subsection 4.2.

In such a model, we assume a driver makes a decision based on the utility of the current location and time by comparing it with the outside option (normalized to 0). Based on the assumption of type I extreme value distribution of the error term, we derive the choice probability as the logit function form:

$$P_{ijt}(Stay) = \frac{exp(U_{ijt})}{1 + \exp(U_{ijt})}. \tag{11}$$

In this case, the likelihood of observing a choice, $A_{ijt} = (Stay_{ijt}, Leave_{ijt})$, can be expressed as:

$$L(A_{ijt}) = \left(\frac{exp(U_{ijt})}{1 + \exp(U_{ijt})}\right)^{Stay_{ijt}} \left(\frac{1}{1 + \exp(U_{ijt})}\right)^{Leave_{ijt}}. \tag{12}$$

Here, $Stay_{ijt} = 1$ if driver i chooses to stay in j during the entire 10-minute bin t. $Leave_{ijt}$ is the number of times she/he chooses to leave j. Note $Stay_{ijt} = 0$ and $Leave_{ijt} = 0$ can occur simultaneously when no overlap exist between drivers' GPS trajectory and the focal location during the 10-minute period, or when the taxi is occupied, in which case the driver does not make any choice. Here, we assume each decision is independent, and we derive the overall likelihood as follows:

$$L(A) = \prod_{i}^{I} \prod_{j}^{J} \prod_{t}^{T} L(A_{ijt}). \tag{13}$$

5. Estimation

In this section, we discuss how we estimate the model and identify all parameters.

5.1. Estimation Methods

To estimate our homogeneous model, we follow Erdem and Keane (1996) and apply the simulated maximum likelihood (SML) method. The Monte Carlo simulation draws signal samples, which we use to apply the Bayesian updating rules to compute the utility, and then compute the simulated likelihood values.

To estimate our heterogeneous model, one challenge is to identify the individual-specific parameters, $\Theta_i = (\beta_i, \delta_i, log(\sigma^2_{Pick,i}), log(\sigma^2_{Drop,i}), log(\sigma^2_{Drive,i})))$. Following Huang et al. (2014) and Netzer et al. (2008), we apply the Metropolis-Hasting algorithm to estimate the individual parameters in a hierarchical framework. Eq. (6) and eq. (7) show that not only is $\tilde{Q}_{ijt}$ stochastic, but also Q_{ijt}, because Q_{ijt} is a function of the three stochastic variables: pick-up, drop-off, and drive-by signals.

We assume all these variables follow normal distributions. We can derive the distribution of Q_{ijt} conditional on $Q_{ij,t-1}$ as

$$Q_{ijt}|Q_{ij,t-1} \sim N(\bar{Q}_{ijt}, v_{ijt}^2). \tag{14}$$

where

$$\bar{Q}_{ijt} = \frac{\sigma_{ijt}^2}{\sigma_{ij,t-1}^2} Q_{ij,t-1} + \left(d_{PU,ijt} \frac{\sigma_{ijt}^2}{\sigma_{Pick,i}^2} + d_{DO,ijt} \frac{\sigma_{ijt}^2}{\sigma_{Drop,i}^2} + d_{DB,ijt} \frac{\sigma_{ijt}^2}{\sigma_{Drive,i}^2} \right) \cdot Q_j \tag{15}$$

and

$$v_{ijt}^2 = d_{PU,ijt} \frac{\sigma_{ijt}^4}{\sigma_{Pick,i}^2} + d_{DO,ijt} \frac{\sigma_{ijt}^4}{\sigma_{Drop,i}^2} + d_{DB,ijt} \frac{\sigma_{ijt}^4}{\sigma_{Drive,i}^2} \tag{16}$$

Equation (8) shows the variance of belief on unobserved demand, σ_{ijt}^2, is a deterministic variable conditional on the variances of the three signals, last-period variance, and frequencies of receiving signals. Thus, conditional on all the parameters of the model, the mean and variance of the normal distribution in eq. (15) are not stochastic. Thus, the individual belief about unobserved demand in any period can be drawn from the following hierarchy:

$$\begin{aligned}
&Q_{ijt}|Q_{ij,t-1} \sim N(\bar{Q}_{ijt}, v_{ijt}^2) \\
&Q_{ij,t-1}|Q_{ij,t-2} \sim N(\bar{Q}_{ij,t-1}, v_{ij,t-1}^2) \\
&... \\
&Q_{ij1}|Q_{ij0} \sim N(\bar{Q}_{ij1}, v_{ij1}^2).
\end{aligned}$$

Therefore, based on the previous assumptions, the hierarchical model can be specified as

$$\begin{aligned}
&\Theta_i|\Psi, Z_i, A_i, \Lambda, \Sigma_\Theta, X_i, Q_i \\
&\Lambda|\Theta_i, Z, \Sigma_\Theta \\
&\Sigma_\Theta|\Theta_i, Z, \Lambda \\
&\Psi|X, Q, \Theta_i \\
&Q_t|Q_{t-1}, Q_{t+1}, A_t, \Theta_i, \Psi.
\end{aligned}$$

We use a MCMC method (Markov chain Monte Carlo) to make draws from the joint posterior distribution of parameters (α and Σ_Θ). Furthermore, for those parameters ($\{\Theta_i\}$, Ψ and Q) for which the full conditional distributions are not easily and directly drawn, we use the Metropolis-Hastings algorithm. We provide the full details of the conditional distributions and the sampling algorithm in the appendix.

5.2. Identification

The true value of unobserved demand Q_j is identified by drivers' steady-state behavior. In the Bayesian learning process, the belief Q_{ijt} evolves to the true demand Q_j. In the extreme case where the state is stable, the demand belief is the true demand. However, following the discussion in Ching et al. (2013), we cannot identify Q and δ simultaneously. To address this issue, we need to either fix Q_j for one alternative j (e.g., Erdem and Keane (1996)) or fix the coefficient δ (e.g., Hao et al. (2014)). Either way, the relative values, rather than the absolute values of unobserved demand, matter. In this paper, we fix Q_j for one j.

The learning parameters Q_0, σ_0^2, $\sigma_{Pick,i}^2$, $\sigma_{Drop,i}^2$, and $\sigma_{Drive,i}^2$ capture how the arrival of signals change the individuals' belief about the demand distribution (i.e., σ_{ijt}^2 and Q_{ijt}). The preference parameter β_i captures individual driver's heterogeneous preferences in evaluating spatial and temporal demand. Note these two sets of individual-specific parameters capture the heterogeneity in both individual preferences and the learning processes. They can be jointly identified because we observe the difference in individuals' decisions as well as the difference in their decision changes over time. More specifically, individual heterogeneous preferences can be identified through variations in decisions from different drivers who had the same information set about a location at a time (i.e., same static location features, same belief about unobserved demand distribution) but made different choices (stay/leave).

On the other hand, the heterogeneity in learning (i.e., individual-specific variances of signals, $\sigma_{Pick,i}^2$, $\sigma_{Drop,i}^2$, and $\sigma_{Drive,i}^2$) can be identified through variations in individuals' decision changes over time, given that they drove by the same location at the same time, and were exposed to the same information signals. In particular, the extent to which, the arrival of signals alters individual behavior over time helps us identify the learning parameters. For instance, if upon the arrival of one signal, ceteris paribus, driver A's behavior is altered much more dramatically than driver B's, we can assume the variance of the signal is much smaller for driver A than for driver B. In other words, this signal is more valuable to driver A than to driver B.

In addition, for tractability in this study we assume the prior mean (Q_0) and variance (σ_0^2) of the perceived distribution of the unobserved demand to be common across individuals and locations. We identify them through the variations in the population-level average behavior change before and after receiving the signals. For example, if after receiving a few pick-up signals at a certain location and time, the driver's probability of staying does not change significantly compared to the initial probability of staying before receiving any signal, then we can assume the prior belief about demand is quite precise and the prior variance is low. Moreover, we also observe variations in the average behavior change during early time periods when drivers may not receive any signal at all. This additional type of variations allows us to further pin down the prior variance. For example, if drivers' behaviors change significantly even without being exposed to any information signal, the prior variance of their belief is likely quite high.

6. Empirical Results

In this section, we discuss our model estimation results. We first present results based on a homogeneous model where every driver shows the same preference. Then, we discuss our results from the heterogeneous model where we relax the assumption by considering driver heterogeneity in the behavior.

6.1. Results of Homogeneous Model

We first present the parameter estimates of the homogeneous model. As we discussed in the previous section, due to identification issue, we need to fix the true unobserved demand of one "product," Q_j. In addition, the utility function requires the unobserved demand to be below a certain level so that utility can be constrained within a proper range. Thus, we set the true unobserved demand in the shopping area at midnight (i.e.,Q_1) to be 1 initially, and update it at each step of MLE (maximum likelihood estimation) process while keeping relative values fixed. This approach is standard in the literature for estimation of Bayesian learning models (Erdem and Keane (1996), Ching et al. (2013)).

Table 2 shows the estimates of the homogeneous parameters in the utility function and learning process. The first three rows are the estimates of the three coefficients in the utility function (eq. (9)), including weights of unobserved demand (δ), POI density (β_1), and the number of intersections labelled as the given type (β_2). First, the estimated weight of unobserved demand (δ) is positive, indicating that larger unobserved demand suggests a higher value of the given location, which increases the probability of a driver's staying in the current grid. Meanwhile, the variances of signals evaluate the precision of the information messages. The estimates of three variances, $log(\sigma^2_{Pick})$, $log(\sigma^2_{Drop})$, and $log(\sigma^2_{Drive})$, are -1.2981, 8.6276, and 0.9281, respectively. Comparison among the three variances shows that, on average, the pick-up signal provides the most precise information. On the contrary, the drive-by signal and drop-off signal are relatively noisy. A noisy signal with a large variance will prohibit drivers from inferring the true demand quickly. This result is intuitive because the drive-by signal requires further inference of the potential starting location and time of the upstream demand, and the drop-off signal also requires inference of potential time gaps between the current pick-ups and the future demand. Therefore, the drive-by signal and drop-off signal inherently bring more uncertainty when being processed. On the other hand, the pick-up signal is the most straightforward because it does not require any further inference; hence, it is more precise on average. Interestingly, for the drop-off signal, beside a high variance the standard error of the estimate is large too (i.e., 24.1172). Such a large standard error indicates that some

Table 2 Homogeneous Model Parameters Estimates

Notation		Parameter estimates
Coefficient-demand	δ	**0.4023** (0.0263)
Coefficient-POI density	β_1	**-0.4973** (0.0042)
Coefficient-# of intersections	β_2	**1.5401** (0.1754)
Pick-up signal variance	$log(\sigma^2_{Pick})$	**-1.2981** (0.2102)
Drop-off signal variance	$log(\sigma^2_{Drop})$	8.6276 (24.1172)
Drive-by signal variance	$log(\sigma^2_{Drive})$	**0.9281** (0.1182)
Initial variance	$log(\sigma^2_0)$	**-1.4740** (0.0701)
Prior belief	Q_0	**2.4467** (0.0712)

Notes:

Standard errors are shown in parenthese.

Bold estimates are significant at the 5% level.

heterogeneity may exist at the individual level, such that the learning process varies among drivers. Finally, the last two rows present the estimates of prior beliefs (Q_0) and prior variance (σ_0^2). The estimate of $log(\sigma_0^2)$ is -1.4740, which means the initial variance, σ_0, is $exp(-1.4740) = 0.2290$. It indicates the variance of drivers' initial prior knowledge is relatively low.

Table 3 shows the estimates of unobserved demand of each location type at four time-of-day periods. Note that due to the identification concern in our estimation, we fixed the demand in the shopping area at midnight as the baseline. Hence, all the estimates are relative values compared to this baseline. As Erdem and Keane (1996) pointed out, the statistically significant levels of these estimates are not a critical issue, but instead, the relative scale of these estimates matters. Overall, our findings show strong evidence that significant heterogeneity exists in city demand across both spatial and temporal dimensions. For example, the demand in the shopping area in the evening and at midnight is significantly larger than during the other two time periods. This finding is consistent with the fact that most shopping stores have their highest visitor volume in the evening after people get off work. In addition, the continuous high demand from evening to midnight implies the increasing needs for taxis may happen in the late rather than early evening. Interestingly, the office area shows the highest demand at midnight, possibly because taxis might not be the main

Table 3 Estimates of True Unobserved Demand (Homogeneous Model)

	Midnight	Morning	Afternoon	Evening
Shopping area	0.4256	**-0.4519**	**-1.7621**	**0.2483**
	(fixed)	(0.1537)	(0.0383)	(0.1043)
Entertainment area	**2.6873**	**2.9490**	**3.3779**	**2.8695**
	(0.1227)	(0.1587)	(0.0676)	(0.1509)
Office area	**2.7299**	**1.3530**	**2.1040**	**0.7125**
	(0.1232)	(0.2076)	(0.0319)	(0.1802)
Residential area	**2.2435**	**2.2096**	**1.7967**	**1.1277**
	(0.1301)	(0.1518)	(0.2039)	(0.1436)
Transportation hubs	**2.4354**	**2.9001**	-0.1754	**2.8630**
	(0.2190)	(0.3184)	(0.1531)	(0.2459)
Others	**-1.4071**	**-0.7770**	**-0.1330**	**-0.6506**
	(0.0850)	(0.0613)	(0.0773)	(0.0598)

Notes:

Standard errors are shown in parenthese.

Bold estimates are significant at the 5% level.

choice for people during their regular home-work transportation time periods (early morning or late afternoon), but taxis become essential when people need to work overtime.

6.2. Results of Heterogeneous Model

In this section, we further relax the assumption to allow for individual-level heterogeneity in drivers' learning process. First, we present the estimates of the parameters that do not vary across individuals (i.e., pooled parameters) in Table 4. The estimates show the common initial variance is very large compared to the absolute value of prior belief. This result indicates the prior belief of the unobserved demand is quite noisy even after accounting for the individual heterogeneity.

Table 4 Pooled Parameter Estimates

Parameters		Parameter estimates	Posterior Std.err.
Initial variance	$log(\sigma_0^2)$	**7.4880**	0.6982
Prior belief	Q_0	**-0.1320**	0.0954

Notes:

To avoid correlation among draws, we use every 50^{th} draw to compute the posterior standard errors.

Bold estimates are significant at the 5% level.

Then we demonstrate the estimation results of the individual-level parameters in Table 5. Recall that we assume each individual-specific parameter is a linear function of individual driver characteristics: $\Theta_i = \Lambda_0 + \Lambda_Z Z_i + \varepsilon_{\Theta_i}$. We include two features in Z_i: company indicators and hourly income levels. In the table, columns 2-4 provide the estimates of the interaction terms of constant (Λ_0) and two observed individual characteristics (Λ_Z). The last column is the standard deviation among individuals, which captures the effects of unobserved individual heterogeneity beyond Z_i. In other words, it shows the square root of the diagonal elements of the variance-covariance matrix Σ_Θ ($\varepsilon_{\Theta_i} \sim N(0, \Sigma_\Theta)$.

Table 5 Individual-level Parameter Estimates

Parameters		Constant	Company Indicator	Income level	Unobserved Heterogeneity†
Coefficient-demand	δ	-0.1103 (0.3746)	-3.5604 (7.5951)	1.6599 (9.5827)	0.6338 (0.2576)
Coefficient-POI density	β_1	0.1529 (0.2988)	5.1673 (5.7766)	1.0919 (9.9402)	0.9119 (0.1019)
Coefficient-# of intersections	β_2	0.0016 (0.0028)	0.0380 (0.0594)	**0.6006** (0.3163)	27.3822 (2.9497)
Pick-up signal variance	$log(\sigma^2_{Pick})$	-0.2888 (0.2789)	**6.5421** (2.6030)	**5.6225** (2.7347)	6.3822 (0.9807)
Drop-off signal variance	$log(\sigma^2_{Drop})$	-0.1131 (0.2096)	**-2.2746** (1.7026)	**-3.8801** (1.9818)	219.5718 (23.6965)
Drive-by signal variance	$log(\sigma^2_{Drive})$	-0.0013 (0.0021)	**-0.0237** (0.0154)	**0.0425** (0.0180)	8.6101 (1.3646)

Notes:

Posterior standard errors are shown in parentheses.

To avoid correlation among draws, we use every 50^{th} draw to compute the posterior standard errors.

Bold estimates are significant at the 5% level.

† This column shows the square root of the diagonal elements of the variance-covariance matrix. It captures the effects of unobserved individual heterogeneity.

Similar to the format of Table 3, the first three rows in Table 5 present the weights in the utility function. And the last three rows present the variances of the three signals. Our estimation offers several interesting findings: First, the estimates in the "constant" column are the average values among all drivers.[9] Among the three signals, the pick-up signal has the lowest mean variance, whereas the drive-by signal has the highest mean variance. This finding indicates that, on average, the simple signal (i.e., pick-up) is more valuable to individual drivers, whereas the complex signals (i.e., drop-off and drive-by) are rather noisy. The heterogeneous results are consistent with the

[9] We performed several robustness tests with different transformations of the individual hourly income, including the original value, the normalized value, demean value, and so on. All the results are consistent.

homogeneous results: different information signals from various social contexts have different values to the drivers in learning the city demand.

Second, interestingly our finding indicates significant heterogeneity across drivers with regard to their learning behavior. The degree of heterogeneity varies among the three signals. The interaction coefficients, shown in the columns labelled "Company Indicator" and "Income Level," indicate the effects of the two individual demographics on the logarithm values of signal variances. Specifically, a *negative* interaction coefficient means that the increase of individual hourly income (or a large company indicator) leads to a *decrease* in the signal variance, indicating the information from the signal is *more precise*. For example, for the drop-off signal, we found its interaction coefficients are both negative (-2.2746 and -3.8801). Therefore, compared to drivers with lower incomes or from smaller companies, drivers with higher incomes or from larger companies tend to process the drop-off signals more effectively and learn the true city demand more quickly. In this way, such drivers with better learning skills will be more likely to choose a location with higher demand and find the next passengers sooner.

Mathematically, the interaction coefficient indicates the learning difference between drivers with higher incomes (or from larger companies) and drivers with lower incomes (or from smaller companies). For example, for the drop-off signal, the interaction coefficient of the company factor is -2.2746. In other words, all else being equal, the value of the drop-off signal for a driver from a small taxi company is only $exp(-2.2746) = 0.1028$ (approximately 1/10) of that signal value for a driver from a large company. Similarly, for the drop-off signal, the interaction coefficient of the income factor is -3.8801, which indicates the value of the drop-off signal for a low-income driver is only $exp(-3.8801) = 0.0206$ (approximately 1/50) of that signal for a high-income driver. In other words, a high-income driver is about 50 times more efficient than a low-income driver in learning true demand information from the drop-off signals.

In comparing the three signals, we find the pick-up signal's interaction terms with income and the company indicator are both significantly positive. However, the drop-off signal's interaction terms with the two individual characteristics are significantly negative. These results seem to suggest that being able to learn local demand from straightforward information, such as pick-up signal, is not as difficult for drivers. Drivers seem to benefit little from such simple signals. Instead, drivers with higher incomes or from larger companies benefit largely from the ability to learn from more complex information, such as drop-off signal. Interestingly, the economic scale of the drive-by signal's interaction terms with the two individual characteristics is very low. This finding indicates low heterogeneity in learning from the drive-by information across individual drivers, possibly because the drive-by information is too noisy at the individual level and no one can benefit much from it.

Table 6 Estimates of True Unobserved Demand (Heterogeneous Model)

	Midnight	Morning	Afternoon	Evening
Shopping area	0.0021	**-2.2606**	**-0.3730**	**1.8320**
	(fixed)	(0.0082)	(0.0134)	(0.0120)
Entertainment area	**1.7514**	**-1.6036**	**-1.7573**	**-0.1405**
	(0.0403)	(0.0263)	(0.0318)	(0.0827)
Office area	**0.4962**	**-0.7494**	**-0.1697**	**-1.0776**
	(0.0508)	(0.0259)	(0.1828)	(0.0196)
Residential area	**-0.4085**	**1.5131**	**0.2962**	**0.2539**
	(0.0536)	(0.0324)	(0.0372)	(0.0413)
Transportation hubs	**0.1456**	**0.6953**	**1.0713**	**2.0209**
	(0.0682)	(0.1401)	(0.1736)	(0.0198)
Others	**-0.4630**	**-0.2508**	**0.0516**	**0.2020**
	(0.0157)	(0.0105)	(0.0120)	(0.0104)

Notes:

Posterior Standard errors are shown in parenthese.

Bold estimates are significant at the 5% level.

To avoid correlation among draws, we use every 50^{th} draw to compute the posterior standard errors.

Third, the estimate of Σ_Θ is shown in the last column of Table 5. It is different from the first three columns because it shows the square root of the diagonal elements of the variance-covariance matrix. It captures the effects of unobserved individual heterogeneity (which income and the company indicator cannot explain). Our results show that even after we control for the observed individual characteristics, significant unobserved heterogeneity still exists in driver learning.

Similar to the homogeneous model, we also provide the estimates of the true unobserved demand of each location at four time-of-day periods in Table 6. In general, they are qualitatively consistent with the estimates from the homogeneous model.

7. Policy Simulations

We conduct four sets of policy simulations to examine the counterfactual effects based on the estimates from our structural model. We average all the final simulation results across 1,000 simulation iterations.

7.1. Information Sharing

In our model, we assume drivers update their beliefs about the demand distribution only through the signals they observe on their own. However, since the taxi companies have access to the GPS traces, what are the implications of the company or policy makers broadcasting all the information signals to everyone (so that the drivers do not have to directly observe the signals by themselves)?

Does this improve drivers' decision-making efficiency? We ran the simulations by allowing for the information sharing with each of the signals separately. The results are shown in Figure 5.

First, all drivers learn much faster in all three cases, indicating the aggregating information signals are valuable to individual drivers. Second, we find the drive-by signals become the most valuable in helping drivers learn demand if we broadcast it. This finding is really interesting because at the individual level, this information is in fact rather noisy and not so valuable for driver learning. One possibility of this policy result is that the frequency of drive-by signals at the population level is much higher than the other two signals. Therefore, although this information is noisy at the individual level, it can become highly informative after we aggregate it over a large scale cross multiple companies, locations, and time periods. Note that unlike pick-up or drop-off which can be inferred from trip-records data, without the offline trace data, the set of drive-by information would NOT have been observed. This finding reinforces one major advantage of our study: that we are able to show the value of aggregating information that would have been otherwise unavailable within a traditional organizational setting to improve decision-making.

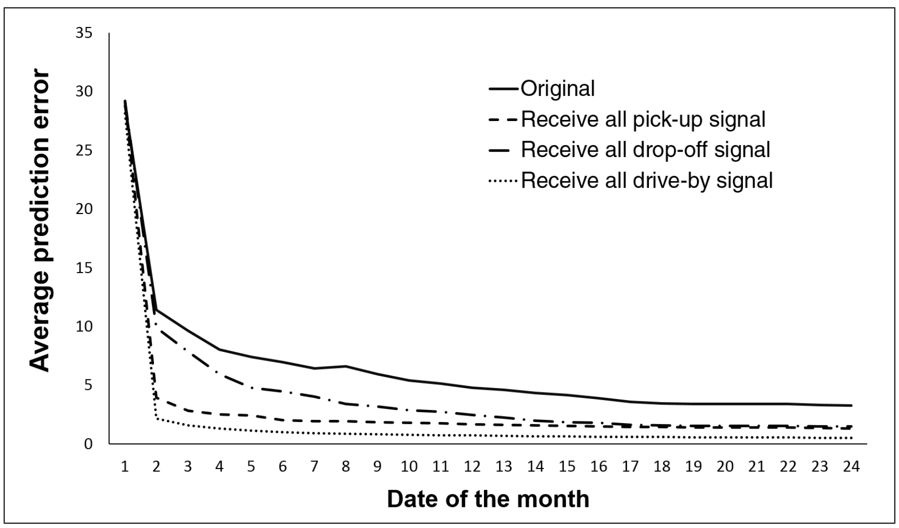


Figure 5 Broadcast Different Types of Information

7.2. Effective Distance of Information

In the previous section, we discussed the simulated results of broadcasting all information signals among drivers across all distance ranges. This strategy can significantly improve drivers' predictions of taxi demand, but it might be costly in operation and the individual drivers are also unlikely to efficiently handle a large volume of information at once, due to cognitive limitation. However, what information-sharing strategy would be more efficient, and what distance range for information sharing would be more optimal is not clear. Thus, we conduct further policy simulations by exploring the effective distance of the information sharing in this section. We provide the results in Figure 6. The x-axis is the number of nearest grids for information broadcasting; the y-axis is the increase in drivers' prediction precision for demand during the first two days.[10].

First, we find that overall, the prediction precision demonstrates an increasing trend as the distance range (scale) of information sharing increases. However, interestingly, the graph indicates the prediction precision does not increase monotonically. More specifically, all three demand signals (pick-up, drop-off, drive-by) show their first peaks at the first-degree (i.e., number of nearest grids equals to 4) or second-degree (i.e., number of nearest grids equals to 10) adjacent grids. We observe a sharp increase in the precision of demand prediction from the starting point to the first-/second-degree adjacent grids. This finding indicates that compared to using demand-information signals observed only within the current local grid, aggregating additional demand information signals from the closely adjacent grids are particularly valuable to drivers for decision making.

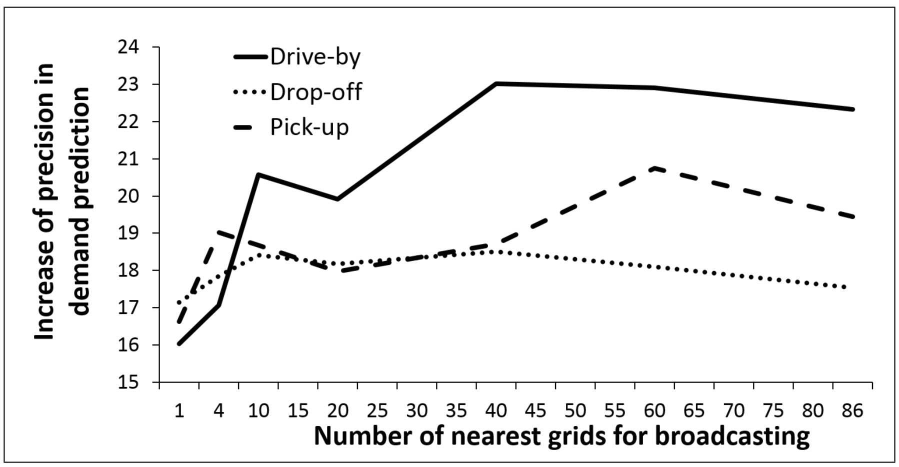


Figure 6 **Simulation Results:Effective Distance Based on Three Signals**

However, at this point, the information sharing is on a relatively small scale. As we start broadcasting the demand signals across more grids that are further away, we observe a slight drop in the precision of driver prediction for demand when approaching the mid-range distance (i.e., number of nearest grids equals to 20-25). This finding seems to suggest more demand signals may not always lead to more efficient decision making. For example, the additional information obtained from the grids with mid-range distance might not be directly relevant to help infer local demand, but instead, the increase in the information scale may add to the variance of the demand signals, which might in turn hinder the drivers' learning process. Interestingly, when we further increase the scale of information sharing to an even larger distance range (i.e., beyond fourth-/fifth-degree

[10] We have also tried different time periods, for example, the first week, the first two weeks, and so on. The results stay highly consistent.

adjacent grids with the number of nearest grids equals to 40-60), we find the precision in drivers' learning about demand increases again. This finding is interesting and suggests that when the scale of information becomes large enough, the value of information might outweigh the potential noise.

In sum, the accuracy of the demand prediction does not increase monotonically with the scale of information being shared. Our results suggest that broadcasting the most adjacent demand signals (first-/second-degree) for drivers seems to be the best strategy if we consider the cost of aggregating signals on a large scale (beyond fourth-/fifth-degree).

Second, with the increase in the number of nearest grids for information sharing, we found the drive-by signal is the most beneficial, whereas the drop-off signal does not seem to show any significant changes. This result implies the value of aggregating information from a large to an even larger scale may vary for different types of information. The drive-by signal is relatively noisy on a small scale, and it can become effective when being aggregated across a considerably large scale. On the other hand, the pick-up signal or drop-off signal are more precise on a small scale. Hence, the marginal value of aggregating such information on a large scale is low. Our findings have the potential to help policy makers better utilize the value of different information to facilitate personalized information sharing and decision making in the market. For example, taxi companies may consider providing all the drive-by information in the city to the individual drivers (via mobile app or phone dispatch). But if they plan to provide pick-up or drop-off information, they may consider providing only the adjacent signals instead of the overall signals to the individual drivers to reduce the operation costs as well as drivers' cognitive costs.

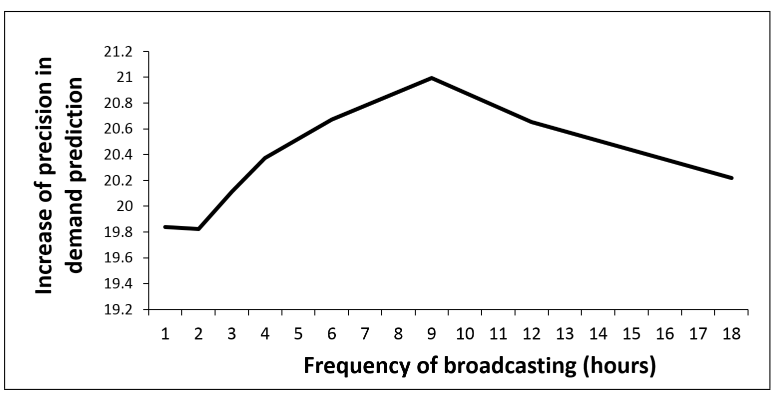


Figure 7 **Simulation Results:Frequency of Broadcasting and Updating**

7.3. Effective Frequency of Information Update

In addition to the spatial concern about broadcasting, temporal factors would also affect the efficiency of broadcasting. This policy simulation is aimed to test the optimal frequency of information update. Figure 7 shows the relationship between the time gaps of broadcasting demand-information signals and the total decrease in the distance between the predicted demand and true unobserved demand during the first six days. Interestingly, we find the prediction precision does not increase monotonically with the frequency of broadcasting. Instead, the performance is best when the signals are broadcast every nine hours. Our result indicates the value of information may not always increase when the update of information becomes more frequent. Therefore, businesses and organizations must understand the incremental value of acquiring larger-scale information across spatial and temporal dimensions in order to better facilitate decision making.

7.4. Income and Welfare Impact

The above three subsections suggest that information sharing can improve the efficiency of driver learning. To further understand the value of information on driver welfare, we examine the impact of information sharing on drivers' economic outcomes (e.g., daily incomes). We compare the model-predicted driver daily incomes under different information sharing policies with the observed actual daily incomes. In particular, we calculate the model-predicted incomes for driver i in location grid j at time t as a function of the expected trip incomes:

$$\begin{aligned}\texttt{Predicted\_Income}_{ijt} &= Pr(\texttt{Stay}_{ijt}) \times E(\texttt{Incomes}_{jt}) + Pr(\texttt{Leave}_{ijt}) \times E(\texttt{Incomes}_{j't}) \\ &= Pr(\texttt{Stay}_{ijt}) \times \texttt{TrueDemand}_{jt} \times \texttt{AvgIncomePerTrip}_{jt} \\ &+ Pr(\texttt{Leave}_{ijt}) \times E[\texttt{TrueDemand}_{j't} \times \texttt{AvgIncomePerTrip}_{j't}]\end{aligned}$$

where $\texttt{TrueDemand}_{jt}$ represents the taxi demand in location grid j at time t and can be estimated from our model. $\texttt{AvgIncomePerTrip}_{jt}$ is the average per-trip income in location grid j at time t and is observed from data. j' denotes the driver is at any of the other location grids than the current grid j. Note that without loss of generality, we assume the number of pick-ups in location grid j at time t is linearly correlated with the local true demand.

We computed the predicted driver incomes under information sharing by broadcasting each of the three information signals separately. We then aggregate the predicted incomes over all drivers across location grids and time and compare with the observed total driver incomes at a daily level. In Figure 8, we present the simulated results. For better intuition, the y-axis is normalized to dollar value.

The results indicate that on average the information sharing among drivers can increase the overall driver incomes. Among all three information signals, drive-by signal demonstrates the highest impact in improving driver incomes when being broadcasted. This is consistent with our previous policy simulation results in subsection 7.2. This income policy simulation suggests that information sharing has the potential to increase overall driver incomes in the taxi market.

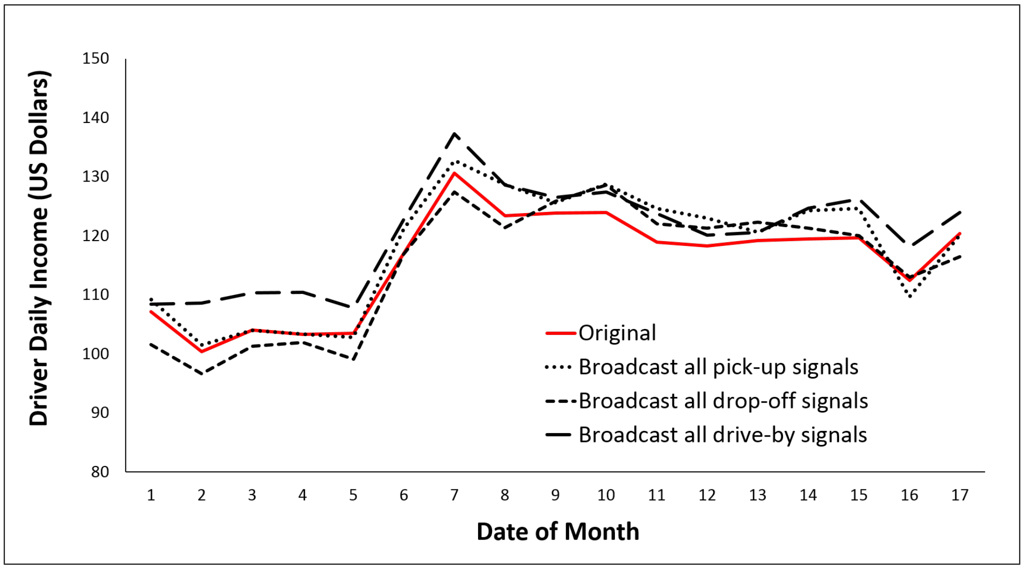


Figure 8 Driver Income Changes with Information Sharing

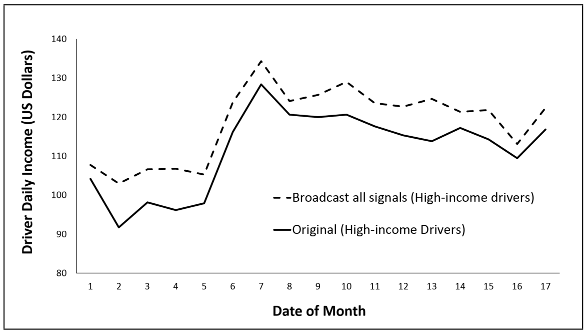
However, it is possible that the information sharing might simply redistribute drivers' incomes (e.g., shifting high-income drivers' incomes to low-income drivers, or vice versa). To further examine the underlying mechanism of the impact and the source of income increase, we separately looked into two types of drivers based on their historical behavior: (1) High-income drivers: drivers with the top 20% highest hourly income and (2) Low-income drivers: drivers with the bottom 20% lowest hourly income.[11] Then, we ran the simulation by broadcasting all three information signals and predicting the overall incomes for the two types of drivers separately. The results are shown in Figure 9. Interestingly, our findings suggest that both high-income and low-income drivers would benefit from information sharing with an increase in the overall incomes.

Finally, to quantify the potential impact on driver welfare, we define the overall driver welfare as the total utilities from all drivers across all location grids and time:

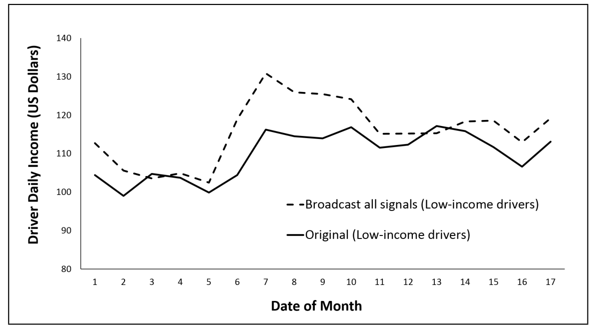
$$\texttt{DriverWelfare} = \sum_{i,j,t} U_{ijt}. \tag{17}$$

We compared the welfare values before and after information sharing (i.e., broadcasting all three information signals) for both high-income and low-income drivers based on our model. Our estimation shows that high-income drivers benefit from a 6.0% welfare increase, while low-income drivers benefit from a 5.5% welfare increase. Our study provides important evidences that efficient information sharing can in fact lead to a welfare increase among all drivers, instead of a welfare shift among different types of drivers. Efficient information sharing can generate additional incomes in the taxi market, which could be missed otherwise.

[11] We also tried alternative definitions by considering different percentiles, such as 30%, 40% 50%. We found our results are very consistent.



(a) High-income Drivers



(b) Low-income Drivers

Figure 9 Income Changes for High-income Drivers and Low-income Drivers by Broadcasting All Signals

8. Conclusions and Discussions

The main goal of this paper is to understand human behavior and decision-making by learning from the large-sale, fine-grained, digitalized offline trace data. We instantiate our study by analyzing the taxi trails to understand drivers' learning behavior for local demand, and to recover the value of information signals extracted from the offline trace. We propose and estimate a structural model to understand individual drivers' heterogeneous learning behavior. We validate our model using a combination of three large, unique data sets containing 10.6 million individual trip records from 11,196 taxi drivers in a large Asian city in September 2009.

Our empirical analyses indicate strong heterogeneity both in the value of information and in individuals' learning behavior about this information. Interestingly, we find straightforward information signal has little value for drivers seeking to gain competitive power. Instead, drivers with higher incomes benefit largely from the ability to learn from more complex information. Our policy-simulation results show that by aggregating the information extracted from the offline behavior trace on a large scale, we can significantly improve individual drivers' decision-making efficiency. Interestingly, we find that information that is noisy at the individual level can become most valuable after we aggregate it across various spatial and temporal dimensions. We also find the marginal value of aggregating larger-scale information varies among different types of information.

Our study demonstrates the value of extracting behavior patterns from granular offline trace data to understand and improve human decision making. In particular, by collecting and analyzing the new source of offline behavior trace, we are able to leverage information that is often unavailable to individuals or organizations in the conventional setting. On a broader note, this work demonstrates the potential of combining large-scale temporal and spatial data mining together with econometric structural models and Bayesian statistics to understand human decision making. With the growing ubiquity of mobile and sensor technologies at the individual level, more and more human behavioral information is digitalized and associated with location and time stamps. Our study can provide a foundation on which future studies can build. Our methodologies can be generalized to other types of vehicle-for-hire demand estimation (e.g., Uber/Lyft) or, more broadly, to other offline settings beyond the taxi industry (e.g., sensor-generated data, Internet-of-Things).

Our paper has a few limitations that can provide potential for future research. First, incorporating more characteristics at the individual-driver level, such as past experience and family background, would be interesting. Our empirical results indicate that significant unobserved heterogeneity still exists. Thus, more individual-level information can help us better explain such heterogeneous variations. Second, our model assumes homogeneous prior belief among individuals. Relaxing this assumption in the future and allowing individuals to vary from the very beginning of the learning procedure would be interesting. In addition, in this paper, we model the individual decision-making problem as a binary discrete choice model (i.e., stay or leave). However, incorporating a multiple-choice model would be more interesting, though it would bring higher computational complexity and burden (e.g., which grid to go next). Lastly, looking into demand shocks in the market and examining how they might affect the taxi industry at the individual-driver level would be interesting. For example, the entry of Uber-type services in the United States. and the adoption of mobile applications have largely affected the taxi markets. Our insights and the structural modeling framework have the potential to be applied in these settings as well.

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Appendix A: Heterogeneous Bayesian Learning Model Estimation

As discussed in the estimation part, the hierarchical model can be specified as

$$\begin{aligned}
&\{\Theta_i\}|\Psi, Z_i, A_i, \Lambda, \Sigma_\Theta, X_j, Q_i \\
&\Lambda|\{\Theta_i\}, Z, \Sigma_\Theta \\
&\Sigma_\Theta|\{\Theta_i\}, Z, \Lambda \\
&\Psi|X, Q, \{\Theta_i\} \\
&Q_t|Q_{t-1}, Q_{t+1}, A_t, \{\Theta_i\}, \Psi.
\end{aligned}$$

Because σ_i, Ψ, and Q_t do not belong to any conjugate family, we apply the mix of MCMC and the Metropolis-Hastings algorithm to estimate those parameters. Each iteration k involves four steps:

(1)Generate Θ_i

The posterior distribution of Θ_i is

$$f(\Theta_i|\Psi, Z_i, A_i, \Lambda, \Sigma_\Theta, X_i, \tilde{Q}_i) \propto |\Sigma_\Theta|^{-1/2} exp[-\frac{1}{2}(\Theta_i - \Lambda Z_i)'\Sigma_\Theta^{-1}(\Theta_i - \Lambda Z_i)]L(A_i)L(Q_i|\{\Theta_i\}) \tag{A.1}$$

and

$$L(Q_i|\{\Theta_i\}) = \prod_{t=1}^{T}\prod_{j=1}^{J} L(Q_{ijt}|Q_{ij,t-1}, \{\Theta_i\}), \tag{A.2}$$

where $L(A_i)$ is the likelihood function. This distribution doesn't have a closed form. Thus, we use the Metropolis-Hastings algorithm to draw a sample with the proportional proposal distribution. Each time, a draw of $\{\Theta_i\}$ is proposed from the proposal distribution. The proposal distribution can be any arbitrary distribution but will affect the efficiency of the estimation. Here, we follow Atchade (2006) and Andrieu and Thoms (2008), and then draw the proposed sample from a normal distribution: $\Theta_i^{k+1} \sim N(\Theta_i^k, \sigma_k^2\Lambda_k)$, where σ_k^2 and Λ_k are chosen adaptively to reduce the autocorrelation among the MCMC draws. The results show the mean of probability of acceptance is around 20%. The probability of accepting Θ_i^{k+1} is

$$Pr(acceptance) = min\left\{\frac{exp[-\frac{1}{2}(\Theta_i^{k+1} - \Lambda Z_i)'\Sigma_\Theta^{-1}(\Theta_i^{k+1} - \Lambda Z_i)]L(A_i|\Theta_i^{k+1})L(Q_i|\{\Theta_i\}^{k+1})}{exp[-\frac{1}{2}(\Theta_i^{k} - \Lambda Z_i)'\Sigma_\Theta^{-1}(\Theta_i^{k} - \Lambda Z_i)]L(A_i|\Theta_i^{k})L(Q_i|\{\Theta_i\}^{k})}, 1\right\}. \tag{A.3}$$

In other words, we always accept the proposed draw when the acceptance is larger than 1, and we reject it accordingly when the acceptance is smaller than 1.

(2)Generate Λ

Λ is the population-level parameter vector that is common among all individuals.

Define $v_\Lambda = vec(\Lambda')$; then

$$v_\Lambda|\{\Theta_i\}, Z, \Sigma_\Theta \sim MVN(u, W), \tag{A.4}$$

where

$W = (Z'Z \otimes \Sigma_\Theta^{-1} + W_0^{-1})^{-1}$,

$u = W[(Z' \otimes \Sigma_\Theta^{-1})\Theta^* + W_0^{-1}u_0]$,

$Z = (Z_1', Z_2', ...Z_I')$ is an $I \times nZ$ matrix of covariates,

$\Theta^* = vec(\Theta')$,

$\Theta = vec(\Theta_1', \Theta_2', ...\Theta_I')$,

u_0 and W_0 are prior hyperparameters, which are specified as

u_0 is a vector of zeros with $length = nZ \cdot n\Theta$,

$W_0 = 100 I_{nZ \cdot n\Theta}$,

$nZ = dim(Z_i)$,

$n\Theta = dim(\Theta_i)$.

(3)Generate Σ_Θ

$$\Sigma_\Theta | \{\Theta_i\}, Z, \Lambda \sim IW\big(f_0 + I, G_0^{-1} + \sum_{i=1}^{I} (\Theta_i^k - \Lambda Z_i)'(\Theta_i^k - \Lambda Z_i)\big), \tag{A.5}$$

where f_0 and G_0 are prior hyperparameters. f_0 is the degree of freedom with predefined value $f_0 = n\Theta + 5$, and G_0 is the scale matrix of the inverse Wishart distribution with $G_0 = I_{n\Theta}$.

(4)Generate Ψ

The conditional distribution of Ψ is defined as:

$$\Psi | X, Q, \Theta_i \propto |V_{\Psi_0}|^{-1/2} exp[-\frac{1}{2}(\Psi - \Psi_0)' V_{\Psi_0}^{-1} (\Psi - \Psi_0)] L(Q|\Psi), \tag{A.6}$$

where Ψ_0 and V_{Ψ_0} are diffused priors. We set Ψ_0 as an $n\Psi \times 1$ vector of zeros and $V_{\Psi_0} = 30 I_{n\Psi}$, where $n\Psi = dim(\Psi)$.

Similarly to the first step, we use a Metropolis-Hastings algorithm to draw Ψ, and the probability of accepting Ψ^{k+1} is

$$Pr(acceptance) = min\Bigg\{\frac{exp[-\frac{1}{2}(\Psi^{k+1} - \Psi_0)' V_{\Psi_0}^{-1} (\Psi k + 1 - \Psi_0)] L(Q|\Psi^{k+1})}{exp[-\frac{1}{2}(\Psi^{k} - \Psi_0)' V_{\Psi_0}^{-1} (\Psi k - \Psi_0)] L(Q|\Psi^{k})}, 1\Bigg\}. \tag{A.7}$$

(5)Generate Q_{ijt}

We sequentially draw Q_{ijt} for each individual i from $t = 1$ to T. Let Q_t denote the matrix of Q_{ijt} on all individuals and all products. The conditional distribution of Q_t is

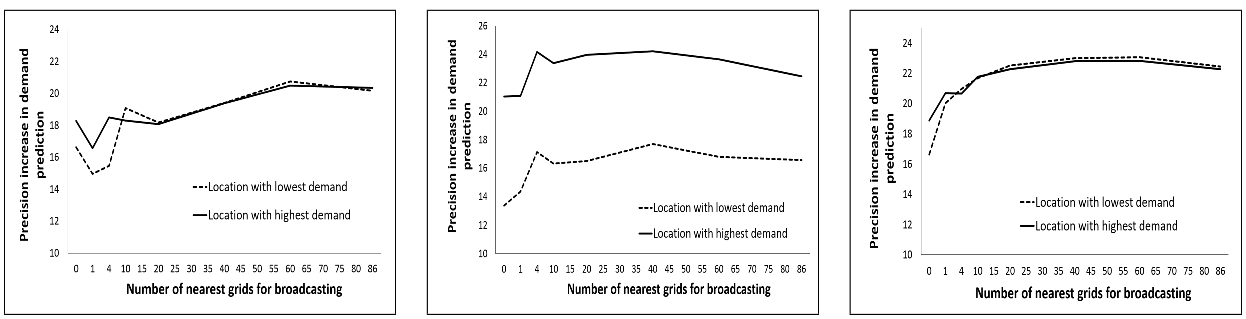
$$f(Q_t | Q_{,t-1}, Q_{t+1}, A_t, \Theta_i, \Psi) \propto L(Q_t|Q_{t-1}) L(A_t|Q_t, \Theta, \Psi) L(Q_{t+1}|Q_t). \tag{A.8}$$

$L(Q_t|Q_{t-1})$ is the likelihood function of Q_t conditional on the last period's draws. The mean and variance of the conditional distribution can be derived from eq. (15) and eq. (16) in section 5. Again, because the posterior distribution doesn't have a closed form, we apply the Metropolis-Hastings methods to draw Q_{ijt}, and the probability of acceptance is

$$Pr(acceptance) = min\Bigg\{\frac{L(Q_t^{k+1}|Q_{t-1}) L(A_t|Q_t^{k+1}, \Theta, \Psi) L(Q_{t+1}|Q_t^{k+1})}{L(Q_t^{k}|Q_{t-1}) L(A_t|Q_t^{k}, \Theta, \Psi) L(Q_{t+1}|Q_t^{k})}, 1\Bigg\}. \tag{A.9}$$

Appendix B: Robustness Check of Demand Density Analysis

In section 7.2, we examined the effective distance of information sharing. Here, in Figure 10, we show the simulated results of the effective distance of information based on locations with the lowest/highest city demand. The three plots present again that signals with different values of information perform differently. For the pick-up signal, the location with the highest taxi demand shows high prediction accuracy compared to the location with the lowest demand, when the first-degree adjacent (i.e., the number of adjacent grids is four) information is broadcast. But with the increase of information being broadcast, the advantage of a high-demand location disappears. However, for the drop-off signal, the gap between a high-demand and low-demand location remains large, one reason of which is that this signal contains large unobserved heterogeneity and thus the negative effect from more noisy information cancels out the positive effect from more signals. Thus, for the drop-off signal, more information would not bring benefits for either low-demand locations or high-demand locations. For the drive-by signal, high-demand and low-demand locations show similar performance. This finding is reasonable because, when broadcast, the drive-by signals have similar volume in high-demand as well as low-demand locations.



(a) Effective Distance (Pick-up) (b) Effective Distance (Drop-off) (c) Effective Distance (Drive-by)

Figure 10 Simulation Results on Effective Distance of Information with Lowest/Highest Demand Locations.

Appendix C: Policy Simulation with Company Size

In our model, we divide companies into two types: large companies and small companies. We find that for drivers from large taxi companies, the complex signal (i.e., drop-off signal) is more valuable than the simple signal (i.e., pick-up signal) in the drivers' learning process. But, in general, will large companies benefit drivers' entire learning process with all three signals? Thus, varying company size and examining what would happen is interesting. In particular, would merging all small companies into large ones improve drivers' learning efficiency by aggregating more resources? We simulate this scenario by assuming that all drivers were from large companies, and present the corresponding result Figure 11. The y-axis is the average discrepancy between true unobserved demand and the individual's perceived demand. The x-axis is the date of the month. Because we assume the initial perceived demand is the same for all individuals, the value of the y-axis indicates how much a driver learns. To illustrate the difference, we show the comparison in the last few days of September 2009. We observe that the dashed line (i.e., simulated case) is slightly below the solid line (i.e., original case), indicating that, on average, drivers perform better if they are all from large taxi companies. This finding implies large companies have a slight benefit in helping drivers learn the city demand. This is potentially due to some unobserved within-company communications.

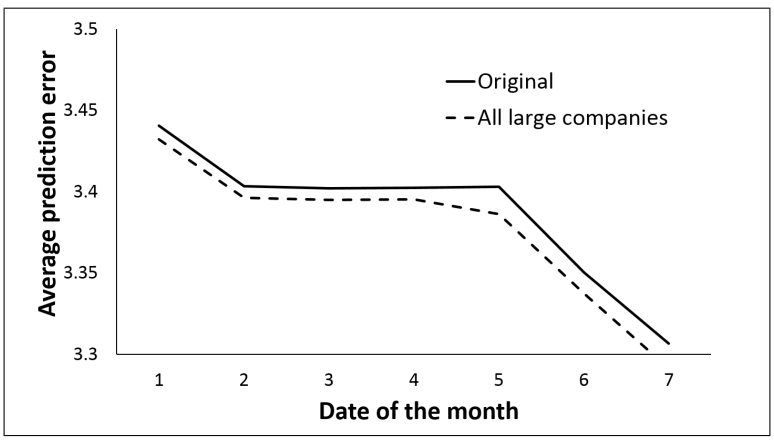


Figure 11 Policy Simulation Result of Company Size