

Learning from the Offline Trace: A Case Study of the Taxi Industry

Completed Research Paper

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Abstract

The growth of mobile and sensor technologies today leads to the digitization of individual's offline behavior. Such large-scale and fine-grained information can help better understand individual decision making. We instantiate our research by analyzing the digitized taxi trails to study the impact of information on driver behavior and economic outcome. We propose homogeneous and heterogeneous Bayesian learning models and validate them using a unique data set containing complete information on 10.6M trip records from 11,196 taxis in a large Asian city in 2009. We find strong heterogeneity in individual learning behavior and driving decisions, which significantly associate with individual economic outcome. Interestingly, our policy simulations indicate information that is noisy at individual level can become most valuable after being aggregated across various spatial and temporal dimensions. Overall, our work demonstrates the potential of analyzing the digitized offline behavioral trace to infer demand as well as to improve individual decision efficiency.

Keywords: Offline behavior; Bayesian learning; heterogeneity; taxi industry; city demand.

Introduction

The recent development of pervasive, interconnected, and smart technologies allows us to digitize our human behavior and interactions at large scale and granular level. Such new sources of information help us to form a holistic view of individual decision making process and to unravel the complexity of human behavior patterns. For example, in the past decade our opinions have been traced as digital word-of-mouth and online user-generated content (UGC). Previous studies have shown significant economic value of such digitized opinion information (e.g., Chevalier and Mayzlin 2006, Ghose et al (2012)). Meanwhile, our online activities such as search and click have been digitized as click-streams data, and our purchase behavior has been traced as digital conversions on search engines like Google, Amazon or Travelocity. Such digitized consumer search-click-purchase information is able to help businesses today infer consumer preferences and choice decisions (e.g., Ghose and Yang 2009; Agarwal et al. 2011; Abhishek et al. 2011; Ghose et al. 2014). Moreover, our social interactions with friends and peers can be traced as digital interactions on online social networks. Previous studies have demonstrated the potential of analyzing digitized social interactions to understand social influence and information diffusion (e.g., Aral and Walker 2011, 2012).

However, existing literature tends to focus mainly on the digitization of user *online* behavior. Such studies have attracted large attention, one reason of which is that online behavior can be easily traced through online cookies, searching logs and other digital sources. However, beyond the online behavior, user *offline* behavior is in fact more informative to reveal individual preferences because most people spend a significant larger amount of time in the offline physical world than in the online virtual world. Moreover, offline behavior involves much higher opportunity cost due to the more complicated social contexts that the users are exposed to. While online users can simply click the mouse to search or choose products, offline users may invest much more time, energy and even pecuniary cost to gain useful information. Thus, offline behavioral traces can provide us with a richer picture about users' preferences towards various social characteristics and deeper insights about their behavior patterns. More importantly, with the increasing pervasiveness of mobile and sensor technologies, as well as the recent emergence of Internet-of-Things (IoT), digitalization of large-scale and fine-grained individual offline behavior becomes feasible. However, it is challenging to track, analyze and understand complete detailed information about individuals' physical behavioral traces (e.g., the offline social and contextual environments users are exposed to; the details of their movements together with temporal and spatial stamps). In this study, we are interested in exploring this emerging domain of information to better understand human behavior and decision making by learning from the digital *offline* traces.

We instantiate our analytics by looking into the real-time taxi trails in urban city environments. Such digital trails allow us to see precisely where, how, and at what time different parts of our cities become stitched together as hubs of mobility. Besides, we also observe the passenger pick-ups and drop-offs, and the taxi income associated with each trail. Taxi drivers' decision-making behavior directly links to their economic outcome and real-time traffic conditions. We aim to extract such knowledge by leveraging information on their physical trace to understand the "micro-level" behavior and the value of information that would otherwise be unavailable to track in the conventional organizational setting. Our study shows the potential of analyzing offline trace information to facilitate individual decision making, as well as to help policy makers identify how to reduce the social and environmental costs in the context of urban and transportation systems.

More specifically, we are interested in recovering the overall city taxi demand by analyzing individual driver-level behavior trace. We aim to examine how taxi drivers learn from different types of social and contextual information at different scales by answering the following three research questions:

- How do taxi drivers infer city demand based on the different information that they are exposed to at different locations at different time periods?
- How do different drivers digest such information differently and how is it associated with their economic outcome?
- How can we leverage the knowledge we learn from the offline trace to improve decision making for both individual users and policy makers?

To address these questions, we propose and estimate a structural model of heterogeneous learning at individual driver level. We validate our study 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: (1) taxi's GPS tracking data (e.g., real-time geographic coordinates and time stamps at minute level); (2) taxi's trip records data (e.g., trip distance, geographic coordinates of pick-up and drop-off location, and paid amount for the trip); (3) static spatial features data (e.g., density of points of interest). The data cover complete information on taxi drivers' GPS trajectory, from which we are able to extract their decision-making behavior and analyze the insights of the behavior pattern.

Our empirical analyses demonstrate some interesting findings: *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, the simple signal (i.e., pick-up signal) is more valuable to individual drivers while the complex signals (i.e., drop-off and drive-by signal) are rather noisy. *Third*, our findings indicate that there is 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 like pick-up signal is not so valuable for drivers to gain high income. Instead, drivers with higher income and from larger companies benefit largely from the ability of learning from more complex information (i.e., drop-off signal). *Finally*, our policy simulation results show that by aggregating the information extracted from the offline behavioral trace at large scale, we can significantly improve individual drivers' decision making efficiency. Interestingly, we find that information that is noisy at individual level can become most valuable after we aggregate it across various spatial and temporal dimensions. We also find the marginal value of aggregating large scale information varies among different types of information.

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 offline trace data to understand and improve human decision making. Especially, by collecting and analyzing the new source of offline trace data, we are able to leverage information that is often unavailable to individuals or organizations in the conventional setting. (2) We develop a Bayesian learning framework to examine drivers' learning process for city demand based on various information they are exposed to. In this model, we distinguish three different information signals extracted from the GPS trace. One methodology innovation of this framework is that we model those three information signals differently in accordance with their contexts. In other words, the learning process is contingent on each driver's own experience and accumulated knowledge to interpret the 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. (3) To the best of our knowledge, this is the first research studying taxi drivers' learning behavior based on utility theory from economics. Such an approach allows us to build linkage between individual behavior and economic outcome from a more explanatory perspective. We can provide insights on how and why drivers behave in certain ways, and how they can be explained by observed and unobserved individual characteristics. (4) 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 behavior. With the growing ubiquity of mobile and sensor technologies at individual level, more and more human behavioral information is digitalized and associated with locations and time stamps. Our study can pave a path for future studies to build on and our methodologies can be generalized to other offline settings beyond the taxi industry.

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 with 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 6, we present our estimation methods and empirical results. Based on the estimates of our structural model, we ran three policy simulation experiments and the results are shown in Section 7. Section 8 concludes this paper with discussions of the contributions of this research, as well as an outline of directions for future studies.

Literature Review

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

First, our study is related to literature on the computational urban analytics. In particular, the availability of real-time GPS tracing data have attracted many researchers from computer science or transportation fields on offline drivers' behavior analytics using machine learning techniques. Existing studies are mainly

divided into two trends: exploratory and predictive analyses. The first category of studies try to explore behavior patterns of taxi drivers (e.g., Camerer et al. 1997; Liu et al. 2010a; Liu et al. 2010b; Liu et al. 2014a; Liao et al. 2006). For example, Camerer et al. (1997) analyzed the relationship between the hours supplied and the changes in taxi drivers' wages. Besides, Liu et al. (2010a) did a comprehensive study with large-scale trace data on several behaviors, including route choice behavior and spatial selection behavior. And Liu et al. (2010b) proposed a new approach called mobility-based clustering to identify hot spots of moving vehicles in an urban area. The second category of studies focus on predictive analysis based on the historical behavior (Liu et al. 2014b; Yuan et al. 2011; Hunter et al. 2009). Specifically, Liu et al. (2014b) used a learning framework by combining own experience with socialized information to study how drivers stay or cruise when seeking next passengers. The social information came from the calls between two drivers and closeness measures between drivers. But how drivers make decisions based on the learned information remained unanswered. Yuan et al. (2011) proposed a system for computing shortest-time driving routes using traffic information and driver behavior. They only used individual behavior to infer the distribution of spatial and temporal travel time without exploring the insights of driver behavior. Most previous studies focused on *how* offline users behave while it remains to be explored about *why* they behave in certain way and *why* they behave differently. To answer these questions, we need to look deeply into the incentives that drive users' behavior. In this paper, we aim to bridge such gap.

Second, 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's paper, Bayesian learning models have been widely used in various fields, including health technology adoption (Hao et al. 2014), crowdsourcing (Huang et al. 2014), wireless service adoption (Iyengar et al. 2007), etc. Within this general framework, there are 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 that 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; Akerberg 2003). (2) Homogeneity versus heterogeneity. Some papers assume that individuals learn in the same way and have the same preferences (Erdem and Keane 1996; Hao et al. 2014), while 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).

Data

We instantiate our research by focusing on the taxi tails. Our empirical study is validated 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. All the data are company-provided. This section describes our raw data, and the detailed process about how we transform the raw data and code our model variables.

Data Description

The empirical analysis is conducted on a combination of three large data sets. First, the taxi behavior trace data contain two real-time data sets: 1) Taxi driver GPS coordinates tracking data and 2) Taxi trip records data. In addition, we supplement these two data sets with the static geographic location data. Our full data set covers all existing companies in the focal city which allows us to infer the overall city demand from the individual taxi trace. This is one advantage of our cross-company data because no single company data can observe all the information signals each driver receives to recover the true spatial and temporal demand.

Taxi driver 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. In this city, due to policy reasons, taxis are divided into three types: *urban* taxis that can only drive within downtown area; *suburban* taxis that can only drive outside downtown area; and *other* taxis that can drive in the whole 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 amount (i.e., total money paid by the passengers) and total distance, taxi company ID and taxi type ID. Combining this data with the GPS tracking data, we have a total of 10.6 million trip records from 11,196 taxi drivers in September 2009.

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

Variable Definition

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

(a) Division of City Plane

We use Voronoi diagrams method (Aurenhammer 1991) to partition the city plane into grids based on the road intersections. Thus, for each road intersection, there is a corresponding location grid closer to that intersection than to any others (Okabe et al. 2009). Then the number of road intersections is exactly the same as the number of location grids in the data set. The drivers are assumed to make decisions and update knowledge of uncertainty at the level of a location grid unit. The road intersection may distribute sparsely in some rural areas. To keep sizes of location grids similar, in this study we focus only on the downtown area of the city (which covers the majority of the taxi demand). This step leads to a total number of 87 road intersections.

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

To define the choice set in this study, we classify the above 87 location grids into six location types according to POIs within each location grid. First, we classify all the 25,317 POIs into different location types based on the keywords in the POI names using supervised learning method¹. Our algorithm identifies six major types of locations: shopping area; entertainment area; office area; residence area; transportation hub and others². However, often times a location grid contains a mixture set of different types of POIs. 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 with a weight vector of the corresponding six location types. The weights are the corresponding probability densities of certain types of POIs within the location grid.

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

Based on the above definitions, we extract two static features from our static geographic data set to control for the popularity of a location. The first feature is POI density. A point of interest (POI) is a specific useful or interesting location for geographic identification. This feature captures the total number of POIs within a location grid. The second feature is the percentage of location grids in the city that belong to the current location type. This feature further captures the overall popularity of a location type.

(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 information allows us to better understand the overall decision process of a driver at a much finer grain (i.e., minute or second level). Note that this granular offline information was usually unobserved in the conventional setting for decision analytics. In particular, we focus on three types of demand signals: pick-up, drop-off, and drive-by. The assumption is that when a driver observes any of these three activities from other peer taxi drivers in the same location at the same time, he/she can gain some additional (but potentially noisy) knowledge about

¹ 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 the unsupervised learning include: topic modeling (Blei et al. 2003), DBSCAN clustering (Ester et al. 1996). However, the results were not satisfying because the names are short and diverse.

² Some POIs contain vague message in their name and hard to be labeled (e.g., parking lots, gas stations). Those POIs have a common feature that they can be in any areas. Thus, we divide them into a separate type called "Others".

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 offline 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 signal from both taxi trip records data set and taxi GPS tracking data set. 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. 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 other drivers' corresponding activities (pick-up, drop-off or drive-by) 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 section³.

(d) Extraction of Choice Decisions

We assume that 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 show that a driver is driving but the corresponding time is not included in any trip record, we define that the taxi is empty at the moment and the driver is seeking passengers. Then, to infer the driver's decision 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, it is *Leave*.

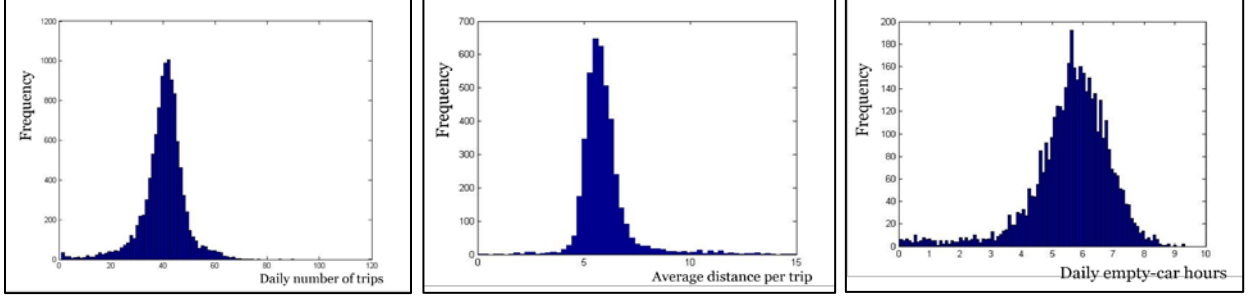
(e) Extraction of Individual Demographics

In the heterogeneous model, we assume that individual-specific parameters are a function of individual demographic features. In this study, we include two different features: Company indicator (i.e., whether the company is larger or not) and income level. Our data covers 109 taxi companies in the focal city. Some companies have significant more taxis than the others. Thus, we divide the companies into two categories: large companies (with more than 200 taxis) and small companies. 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).

Model-Free Evidence

Before modeling the detailed decisions, we would like to explore our data to develop intuition about individuals' behavior. Figure 1 shows that distributions of individual daily number of trips (Figure 1a), average distance per trip (Figure 1b) and average daily empty-car hours (Figure 1c). Each trip represent a taxi pick-up. Distance per trip is the driving distance when the taxi is full. Empty-car hours mean the time when the taxi is empty and the driver is seeking the next passengers. The three plots suggest that there exists significant heterogeneity in taxi drivers' behavior. Figure 2 shows individual's daily number of trips over time (For illustration, we present five randomly sampled drivers in the plot). On average, drivers's daily number of trips increases but the scale of increasing rate is different among individuals. Generally, our data indicates two types of drivers: (i) experienced drivers (shown as solid lines) who behave relatively stable over time with only a small increase in the number of daily trips; (ii) new drivers (shown as dash line) who improve their performance largely 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 2 shows that for each driver on average there seems to exist learning behavior over time. More importantly, there exists significant heterogeneity in drivers' learning behavior. In the next section, we propose a heterogeneous structural model to explain what factors may drive these observations.

³ Note that in our main estimation we use 10-minute time slot as the unit of analysis for driver learning. This is why we extract all the information at 10-minute level here. We discuss more details on the reason behind this definition in the next section. In addition, we have tested other definitions of the time slot, such as 30 minutes, an hour, six hours or a day. We find the results are qualitatively consistent.



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

Figure 1 Distributions of drivers' behavior

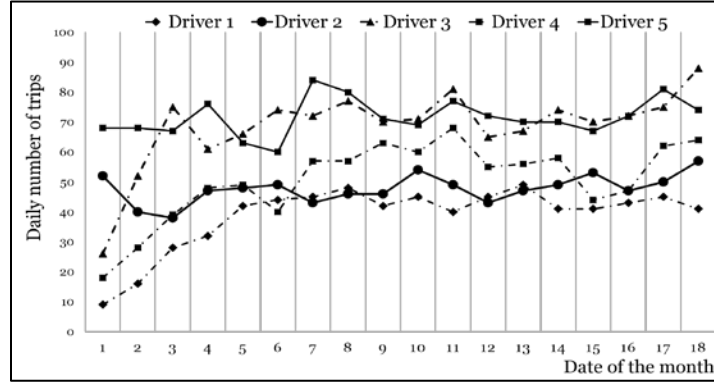


Figure 2 Individual Daily Numbers of Trips over Time

Model

Following Erdem and Keane (1996), we develop a Bayesian learning framework to model how taxi drivers learn the city demand. Such a structural mechanism helps us explicitly model individual decision making process through the utility function. Besides, this model also explains how drivers' uncertainty about the taxi demand is resolved via three different information signals with a Bayesian updating process. To begin with, we first explain individual utility function.

Utility Function

The value of a location for a taxi driver is its potential demand. That is, the higher value a location grid is, the larger probability that the driver can pick up next passenger quickly. Thus, we model the utility a driver gain from a location as a function of demand. However, demand is an abstract concept for drivers and cannot be observed fully and directly from visible factors. On the one hand, some static location features can partially reflect the taxi demand. For example, an area with more buildings may indicate a high population density, which leads to a higher taxi demand. On the other hand, the true demand may only be revealed through drivers' experience because there is uncertainty 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. More formally, utility function is described as follows:

Suppose that there are I individual drivers in the market. Each driver i ($i = 1, 2, \dots, I$) updates his/her knowledge of temporal and spatial demand, and then makes choice decisions among J possible alternative. Each j ($j = 1, \dots, J$) represents a tuple with spatial and temporal elements: $j = (l, \tau)$, where l denotes location grid and τ denotes 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 together with a random shock ε_{ijt} , which captures any idiosyncratic shock during the decision process. We assumed ε_{ijt} to be i.i.d. and to follow type I extreme value distribution:

$$\begin{aligned}
 \tilde{U}_{ijt} &= f(\text{Demand}_{ijt}) + \varepsilon_{ijt} \\
 &= f(\text{ObservedDemand}_{jt} + \text{UnobservedDemand}_{ijt}) + \varepsilon_{ijt} \\
 &= \beta_i X_j + \delta_i \tilde{Q}_{ijt} + \varepsilon_{ijt}
 \end{aligned} \tag{1}$$

As mentioned above, the demand is divided into two parts: observed ($ObservedDemand_{jt}$) and unobserved ($UnobservedDemand_{ijt}$). The observed demand consists of several static spatial features of the neighborhood (X_j). In this study, we consider two features as we introduced in the previous section: (1) POI density; (2) Percentage of location grids in the city that belong to the same location type. The coefficient vector β_i 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 they are exposed to. δ_i captures drivers' preference towards the unobserved demand. The driver is assumed to make decisions based on expected utility value. Thus, this expected utility is:

$$U_{ijt} = E(\tilde{U}_{ijt}) = \beta_i X_j + \delta_i E(\tilde{Q}_{ijt}) + \varepsilon_{ijt} \quad (2)$$

Learning Process in Bayesian Mechanism

To reduce the uncertainty about the true demand, the driver needs to learn through social contexts. We follow standard method of Bayesian learning model by assuming drivers behave 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 minutes⁴. As we discussed in the previous section, we consider three different information signals that a driver is potentially exposed to 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. Thus, if a driver passes a location l with one or more pick-ups during the given 10-minute slot t , we assume that 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 of the unobserved demand at j . Notice that τ is the time-of-day period that contains the given 10-minute unit of time slot for learning update.

However, each driver may not precisely evaluate the messages from pick-up signals. For example, the drivers may not be able to capture all the pick-ups made by the other taxi drivers or the overall pick-ups may be affected by some unexpected random shocks. Thus, similar to previous studies (Erdem and Keane 1996; Huang et al. 2014), we assume that each driver's pick-up signal ($PickS_{ijt}$) follows a normal distribution around the true unobserved demand:

$$PickS_{ijt} \sim N(Q_j, \sigma_{Pick,i}^2), \quad (3)$$

where $\sigma_{Pick,i}^2$ is the variance of the signal which indicates the precision (or value) of the information.

(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 shopping malls at 7pm and go back home three hours later. Thus, the drop-off at 7pm may lead to potential future demand at 10pm. To model such more complex information, we consider the drop-off signal in drivers' learning process. Specifically, suppose a driver passes a location l where there exist one or more drop-offs 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. In other words, $\tau = \tau_0 + \Delta$, where Δ is the time gap between the current drop-off and future pick-up. Similar to the pick-up signal, we also assume that each drop-off signal follows a normal distribution with variance $\sigma_{Drop,i}^2$ which indicates the value of the drop-off information:

$$DropS_{ijt} \sim N(Q_j, \sigma_{Drop,i}^2), \quad (4)$$

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 on the possibility of such transformation. To model this, we use historical data to recover the empirical distribution of the pick-up probability conditional on a drop-off. We assume this is common knowledge for all drivers.

(c) Drive-by Signals

A drive-by full taxi (i.e., with passenger) in a location may not directly reflect the current location's demand. However, it may give us some hints about the demand in the other locations where the taxi

⁴ Our data shows 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 around 10 minutes.

possibly comes from. Thus, if a driver knows where and when the full taxi that drives by may originate from, he/she can update his knowledge of the unobserved demand in that original location and time.

To model this, we first recover the set of all possible starting location and time combinations (j) for each full taxi that drives by. We apply a similar approach as described above for the drop-off signals. In particular, 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, then 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. In other words, $l = l_0 - \Delta l, \tau = \tau_0 - \Delta \tau$, where Δl and $\Delta \tau$ represent the location and time gaps between the current drive-by and the original pick-up.

Similarly, we assume this is common knowledge among all drivers. Notice that 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 leads to larger probability of being as potential starting point of the drive-bys. Again, similar to the previous two signals, each drive-by signal follows a normal distribution with variance $\sigma_{Drive,i}^2$ which indicates the value of the drive-by information:

$$DriveS_{ijt} \sim N(Q_j, \sigma_{Drive,i}^2), \quad (5)$$

(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 distributed normally with mean Q_0 and variance σ_0^2 . And over time the drivers would receive the surrounding signals to update their beliefs about the distribution. By using Bayes rule (De Groot 2005), drivers will update their posterior belief conditional on the prior belief and signals. Because the prior belief at time t_0 and all signals are assumed to be normally distributed, the posterior belief at any time period is also a normal distribution. The posterior belief is given by:

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

where

$$Q_{ijt} = \left[\frac{Q_{ij,t-1}}{\sigma_{ij,t-1}^2} + \frac{d_{PU,ijt} PickS_{ijt}}{\sigma_{Pick,i}^2} + \frac{d_{DO,ijt} DropS_{ijt}}{\sigma_{Drop,i}^2} + \frac{d_{DB,ijt} DriveS_{ijt}}{\sigma_{Drive,i}^2} \right] \cdot \sigma_{ijt}^2 \quad (7)$$

and

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

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 . Then given that the unobserved demand belief 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 re-written as:

$$U_{ijt} = E(\tilde{U}_{ijt}) = \beta_i X_j + \delta_i Q_{ijt} + \varepsilon_{ijt}. \quad (9)$$

Furthermore, we define $\theta_i = (\beta_i, \delta_i, \sigma_{Pick,i}^2, \sigma_{Drop,i}^2, \sigma_{Drive,i}^2)$ as a heterogeneous parameter vector. And the homogeneous parameter vector $\Phi = (\{Q_j\}, Q_0, \sigma_0^2)$ is common among all individuals. 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: $\theta_i = \Lambda_0 + \Lambda_Z Z_i + \varepsilon_{\theta_i}$, where Z_i specifies observed individual-specific characteristics and ε_{θ_i} is unobserved error term with uninformative prior: $\varepsilon_{\theta_i} \sim N(0, \Sigma_\theta)$. Λ_0 is a vector of the mean individual-specific coefficients. 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.

Individuals' Decision Making Problem

Individual drivers make decisions based on their expectation of the utility they derive from each alternative (McFadden 1973). Consistent with the updating process, we assume that 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, they need to decide whether to stay within the same location grid or drive to other locations. If the data shows that a driver stays within the same grid within a 10-minute slot with an empty taxi, the driver is considered as choosing option *Stay*. If a driver with an empty taxi passes more than one grids within the 10-minute slot, the driver is considered as choosing option *Leave*.

In such a model, we assume that 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:

$$P_{ijt}(Stay) = \frac{\exp(U_{ijt})}{1 + \exp(U_{ijt})} \quad (10)$$

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

$$L(A_{ijt}) = \left(\frac{\exp(U_{ijt})}{1 + \exp(U_{ijt})} \right)^{Stay_{ijt}} \left(\frac{1}{1 + \exp(U_{ijt})} \right)^{Leave_{ijt}} \quad (11)$$

Here, $Stay_{ijt} = 1$ if a driver i chooses to stay in j within the whole 10-minute slot t . And $Leave_{ijt} = 1$ if the driver chooses to leave j during 10-minute slot. Notice that it is possible that $Stay_{ijt} = 0$ and $Leave_{ijt} = 0$ occur simultaneously when there is no overlap between driver's GPS trajectory and the focal location during the 10-minute period, or when the taxi is full in which case the driver does not make any choice. Here we assume that each decision is independent and we derive the overall likelihood as follows:

$$L(A) = \prod_i \prod_j \prod_t L(A_{ijt}) \quad (12)$$

Estimation

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

Estimation Methods

To estimate our heterogeneous model, one challenge is to identify the individual-specific parameters, $\Theta_i = (\beta_i, \delta_i, \sigma_{Pick,i}^2, \sigma_{Drop,i}^2, \sigma_{Drive,i}^2)$. 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 \tilde{Q}_{ijt} but also Q_{ijt} are stochastic, because Q_{ijt} is a function of the three stochastic variables: pick-up, drop-off and drive-by signals. We assume all these variables to follow normal distributions. We can derive the distribution of Q_{ijt} conditional on $Q_{ij,t-1}$ as

$$Q_{ijt}|Q_{ij,t-1} \sim N(\bar{Q}_{ijt}, v_{ijt}^2), \quad (13)$$

where

$$\bar{Q}_{ijt} = \frac{\sigma_{ijt}^2}{\sigma_{ij,t-1}^2} Q_{ij,t-1} + \left(d_{PU,ijt} \frac{\sigma_{ijt}^2}{\sigma_{Pick,i}^2} + d_{DO,ijt} \frac{\sigma_{ijt}^2}{\sigma_{Drop,i}^2} + d_{DB,ijt} \frac{\sigma_{ijt}^2}{\sigma_{Drive,i}^2} \right) Q_j, \quad (14)$$

and

$$v_{ijt}^2 = d_{PU,ijt} \frac{\sigma_{ijt}^4}{\sigma_{Pick,i}^2} + d_{DO,ijt} \frac{\sigma_{ijt}^4}{\sigma_{Drop,i}^2} + d_{DB,ijt} \frac{\sigma_{ijt}^4}{\sigma_{Drive,i}^2}. \quad (15)$$

Eq.8 shows that 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.14 are not stochastic. Thus, the individual belief on unobserved demand in any period can be drawn from the following hierarchy.

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

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

$$\begin{aligned} \{\Theta_i\} | \Psi, Z_i, A_i, \Lambda, \Sigma_\Theta, X_i, Q_i \\ \Lambda | \{\Theta_i\}, Z, \Sigma_\Theta \\ \Sigma_\Theta | \{\Theta_i\}, Z, \Lambda \end{aligned}$$

$$\Psi|X, Q, \{\theta_i\}$$

$$Q_t|Q_{t-1}, Q_{t+1}, A_t, \theta_i, \Psi$$

We use MCMC method (Agarwal et al. 2011) to draw from the joint posterior distribution of parameters (Λ and Σ_θ). Furthermore, for parameters ($\{\theta_i\}, \Psi$ and Q) for which we cannot directly draw from the full conditional distributions, we apply the Metropolis-Hastings algorithm (Andrieu and Thoms, 2008).

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). In both ways, 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 $Q_0, \sigma_0^2, \sigma_{pick,i}^2, \sigma_{drop,i}^2$, and $\sigma_{drive,i}^2$ capture how the arrival of signals change individual's 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 that 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 is driver B, it implies that 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.

Besides, 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 probability of staying does not change significantly compared to the initial probability of staying before receiving any signal, then it implies that 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 largely even without being exposed to any information signal, it implies that the prior variance of their belief is quite high.

Empirical Results

As discussed in the previous Section, for the concern of identification issue, we fix the true unobserved demand of one "product", Q_j . Besides, the utility function requires that the unobserved demand below a certain level so that utility is increasing within a proper range. Thus, we set the true unobserved demand of shopping area at midnight (Q_1) to be 1 initially and updated it at each step of MLE estimation process while keeping relative values fixed (Ching et al. 2013; Erdem and Keane 1996).

The estimates of the parameters that do not vary across individuals (i.e., pooled parameters) are presented in Table 1. Here, we assume that individuals have the same prior belief and initial variance for all locations at all time-of-day periods. The estimates show that the common initial variance is very large

compared to the absolute value of prior belief. This result indicates that the prior belief of the unobserved demand is quite noisy even after accounting for the individual heterogeneity.

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

Note:

1. To avoid correlation among draws, we use every 50th draw to compute posterior std. err.
2. Bold estimates are significant at 5% level.

Table 1 Pooled Parameter Estimates

Parameters	Constant	Company	Income	Unobserved
δ	-0.1103 (0.3746)	-3.5604 (7.5951)	1.6599 (9.5827)	0.6338 (0.2576)
β_1	0.1529 (0.2988)	5.1673 (5.7766)	1.0919 (9.9402)	0.9119 (0.1019)
β_2	0.0016 (0.0028)	0.0380 (0.0594)	0.6006 (0.3163)	27.3822 (2.9497)
$\log(\sigma_{pick}^2)$	-0.2888 (0.2789)	6.5421 (2.6030)	5.6225 (2.7347)	6.3822 (0.9807)
$\log(\sigma_{drop}^2)$	-0.1131 (0.2096)	-2.2746 (1.7026)	-3.8801 (1.9818)	219.5718 (23.6965)
$\log(\sigma_{drive}^2)$	-0.0013 (0.0021)	-0.0237 (0.0154)	0.0425 (0.0180)	8.6101 (1.3646)

Note:

1. To avoid correlation among draws, we use every 50th draw to compute posterior std. err.
2. Bold estimates are significant at 5% level.

Table 2 Individual-Level Parameter Estimates

The estimation results of the individual-level parameters are summarized in Table 2. Recall that we assume each individual-specific parameter is a linear function of individual 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 and two observed individual characteristics. The last column is the standard deviation among individuals, which captures the effects of unobserved individual heterogeneity.

There are several interesting findings from our estimation: First, different information signals from various social contexts have different values to the drivers in learning the city demand. Among the three signals, pick-up signal has the lowest mean variance, while drive-by signal has the highest mean variance. This indicates that on average, the simple signal (i.e., pick-up) is more valuable to individual drivers while the complex signals (i.e., drop-off and drive-by) are rather noisy. This result is intuitive because drive-by signal requires further inference of potential starting location and time of the upstream demand, and drop-off signal also requires inference of potential starting time of the future demand. However, pick-up signal is the most straightforward and it does not require any further inference, hence it is more precise on average.

Second, our finding indicates that there is significant heterogeneity across drivers with regard to their learning behavior. The degree of heterogeneity varies among the three signals. Interestingly, for the pick-up signal, we find that coefficients of its interaction terms between pick-ups signal ($\log(\sigma_{pick}^2)$) and income/company indicator are both significantly positive. However, for the drop-off signal, the coefficients of its interaction terms with the two individual characteristics are significantly negative. These results seem to suggest that straightforward information like pick-up signal is not so valuable for drivers if they want to earn high income. Notice that with a negative coefficient of interaction terms, it means that a higher income value (or a large company) leads to a smaller variance of signals, which indicates that the signals are more precise. Instead, drivers with higher income or from larger companies benefit largely from the ability of learning from more complex information like drop-off signal. Interestingly, for the drive-by signal, we find the economic scale of its interaction terms with the two individual characteristics is very low. This finding indicates that there is low heterogeneity in learning from the drive-by

information across individual drivers. This can be simply because the drive-by information is too noisy at individual level and no one can benefit much from it.

Third, the estimate of Σ_{Θ} is shown in the last column of Table 2. Here we present the standard deviations of the unobserved individual characteristic, which are the square root of the diagonal elements of the variance-covariance matrix. It captures the effects of unobserved individual heterogeneity (which cannot be explained by income and company indicator). Our results show that even after control for the observed individual characteristics, there still exists significant unobserved heterogeneity in driver learning.

Finally, Table 3 shows the estimates of the unobserved demand of each of the six location types at four different time-of-day periods. Note that for identification in our estimation we fixed the demand of shopping area at the midnight as the baseline. Hence, all the estimates are relative values compared to this baseline. Notice that as pointed out by Erdem and Keane (1996), the statistical significant levels of these estimates do not matter, but only the relative scale of these estimates matters. Overall, our findings show strong evidence that there is significant heterogeneity in city demand across both spatial and temporal dimensions. For example, the demand of shopping area in evening and midnight is significantly larger than the other two periods. It is consistent with the fact that most shopping stores have their highest visit demand in the evening after people get off work. Besides, the continuous large demand from evening to midnight implies that the increasing needs for taxi may happen in the late evening, rather than early evening. Interestingly, office area shows the highest demand in the midnight. The potential reason is that taxi may not be the main choice for people during their regular home-work transportation time periods (early morning or late afternoon), but it becomes essential when people need to work overtime.

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

Note:

1. To avoid correlation among draws, we use every 50th draw to compute posterior std. err.
2. Bold estimates are significant at 5% level.
3. Posterior standard errors are shown in the parenthesis

Table 3 Estimates of True Unobserved Demand

Policy Simulation

We conduct two sets of policy simulations to examine the counterfactual effects based on the estimates from our structural model. The final simulation results are averaged across 1,000 simulation iterations.

Company Size

In our model, we divide companies into two types: large and small. We found that drivers from large company can extract more valuable information from complex signal (i.e., drop-off signal) better but less valuable information from the simple signal (i.e., pick-up signal). It is interesting to vary company size and examine what would happen. In particular, we are interested if we merged all small companies into large ones, would it improve drivers' learning efficiency by aggregating more resources? We simulate this scenario by assuming that all drivers were from large companies and the corresponding result is shown in Figure 3(a). The y-axis is the average discrepancy between true unobserved demand and the individual perceived demand. The x-axis is date of the month. To illustrate the difference, we show the comparison in the last few days of September 2009. We observe that the dash line is slightly below the solid line, indicating that drivers in the simulated case perform better. It implies that large companies have a slight benefit in helping drivers learn the city demand. This is potentially due to the unobserved within-company communications.

Information Sharing

In our model, drivers are assumed to update their beliefs about the distribution only through the signals they observe on their own. However, if the companies or policy makers were to broadcast all information signals to everyone (so that the drivers do not have to directly observe the signals by themselves), would it 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 3(b).

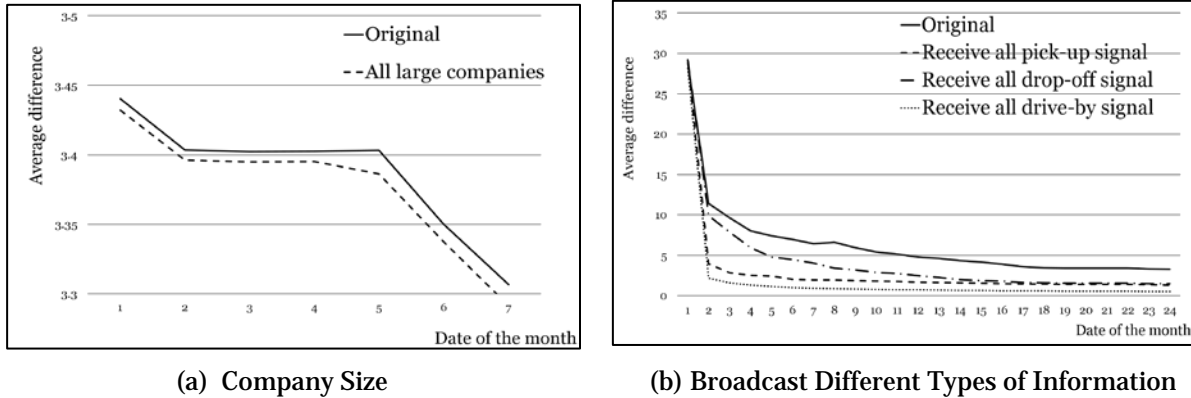


Figure 3: Simulation Results on Company Size and Information Sharing.

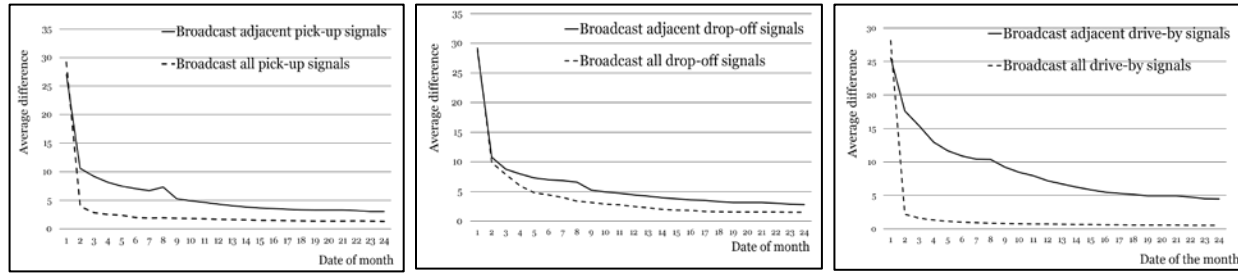
First, all drivers learn much faster in all three cases, indicating that the aggregating information signals are valuable to individual drivers. Second, we find that the drive-by signals become the most valuable to help drivers learn demand if we broadcast it. This is really interesting because at individual level this information is in fact rather noisy and not so valuable for driver learning. The reason for this policy result is potentially because the frequency of drive-by signals at population level is much higher than the other two signals. Therefore, although this information is noisy at individual level, it can become highly informative after we aggregate it over a large scale cross multiple companies, locations and time periods. Notice that not like pick-up or drop-by which can be inferred from trip record data, the set of drive-by information would have been hardly observed to individuals or companies, if not look into offline trace data. 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 traditional organizational setting to improve decision-making.

Effective Distance of Information

Furthermore, we are interested in the effective distance of the information value. Thus, we ran a further policy simulation where only the adjacent signals would be broadcasted. Here, "adjacent signals" mean those signals that occur in the adjacent location grids at the same time when the driver pass a location grid. The results are shown in Figure 4. We present the three signals separately ((4a) is for pick-up signal; (4b) is for drop-off signal; (4c) is for drive-by signal). The y-axis is the average discrepancy between the true unobserved demand and the individual perceived demand. The x-axis is date of the month. The three graphs consistently show that when broadcasting the information signals from all locations drivers will learn more quickly, compared with the case when broadcasting the signals from only the adjacent locations. This result indicates that information aggregated over a larger distance scale is indeed more valuable.

However, interestingly only the drive-by signal (Figure 4c) shows a significant improvement in driver learning efficiency after adding more information beyond the adjacent locations (i.e., difference between the solid line and the dash line in the graph). This result implies that the value of aggregating information from large to even larger scale may vary for different types of information. drive-by signal is relatively noisy in small scale, and it can become effective when being aggregated across a considerably large scale. On the other hand, pick-up signal and drive-by signal are more precise in small scale. Hence, the marginal value of aggregating such information at large scale is low. Our findings have the potential for policy makers on better utilizing 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 individual driver (via mobile app or phone dispatch). But if they plan to provide

pick-up or drop-off information, they may consider only the adjacent signals to the individual driver instead of the overall signals to reduce the operation cost as well as drivers' cognitive cost.



(a) Effective Distance (Pick-up)

(b) Effective distance (Drop-off)

(c) Effective Distance (Drive-by)

Figure 4: Simulation Results on Effective Distance of Information.

Conclusions

The main goal this paper is to understand human behavior and decision-making by learning from the large scale, fine-grained, digitalized offline trace data. We instantiate our study by analyzing the taxi tails to understand driver 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 of heterogeneous learning at individual level. 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 individual's learning behavior towards this information. Interestingly, we find that straightforward information signal is not so valuable for drivers to gain competitive power. Instead, drivers with higher income benefit largely from the ability of learning from more complex information. Our policy simulation results show that by aggregating the information extracted from the offline behavior trace at large scale, we can significantly improve individual drivers' decision-making efficiency. Interestingly, we find that information that is noisy at individual level can become most valuable after we aggregate it across various spatial and temporal dimensions. We also find the marginal value of aggregating large 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. Especially, 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 individual level, more and more human behavioral information is digitalized and associated with location and time stamps. Our study can pave a path for future studies to build on and our methodologies can be generalized to other offline settings beyond the taxi industry (e.g., Internet-of-Things, Uber/Lyft).

Our paper has a few limitations which can provide potential for future research. First, it would be more interesting to incorporate more characteristics at individual driver level, such as past experience, family background, etc. Our empirical results indicate that there still exists significant unobserved heterogeneity. Thus, more individual-level information can help us better explain such heterogeneous variations. Second, our model assumes homogeneous prior belief among individuals. It would be interesting to release this assumption in future and allow individuals vary from the very beginning of the learning procedure. Besides, it would be interesting to look into demand shocks in the market and examine how they may affect taxi industry *at individual driver level*. For example, the entry of Uber and other similar services in U.S. and the adoption of mobile applications have largely affected the taxi markets. Our insights and structural methodology framework have the potential to be applied to such future areas.

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