No Magic for Market Entry in the Field: Evidence from Taxi Markets

Xiaoyu Xia* Juin Kuan Chong†

February 15, 2021

Abstract

We study taxi markets in Singapore to understand market entry in the field. While market entry games in the lab consistently produce equilibrium outcomes, we show that a lack of market knowledge hinders the markets from consistently reaching equilibrium in the field. In Singapore, a small 720-square-kilometre island city that can be divided into 29 taxi markets, full equilibrium is elusive: 68% of the market-entry decisions made by the 2,728 taxi drivers in our data could be improved. Using three months of earnings and detailed movement data from these taxi drivers, we find an average 20% gap in marginal wage rates across markets. We use dynamic programming to derive the optimal solution for more than 3 million search decisions and find that only 32% of the searches ended in an optimal market. Finally, we find that market knowledge developed in a given month explains an additional 3% variation of the earning losses in the 2.6 million decisions for the subsequent two months, an improvement in model fit of 74%; while strategic thinking and minimization risk have no impact on earning loss.

Keywords: market entry equilibrium; taxis; dynamic programming; market knowledge; strategic thinking

*Department of Economics, University of Essex. Email: xiaoyu.xia@essex.ac.uk.

†Department of Marketing, National University of Singapore, Email: bizcjk@nus.edu.sg. The author acknowledges the funding support of the grant MOE2016-SSRTG-059 from the Social Science Research Council of Singapore.

1 Introduction

Market-entry games in the lab offer a glimpse into how actual market entry in the field may turn out. Lab results show that agents coordinate their entry decisions to achieve equilibrium, almost magically (e.g. Rapoport et al., 1998, Erev and Rapoport, 1998). However, the uncontrollable environmental factors and typically limited data availability constrain a meaningful investigation into market entry in the field. Data availability and the homogeneous environment of the taxi markets in Singapore make it a good example for investigating how market entry works in the real world. The focus of this paper is in identifying key factors that might cause disequilibrium in market entry in the field.

Taxi markets in Singapore resemble market-entry games in the lab in two important ways. First, similar to market-entry games, demand and supply in the taxi markets are simple when drivers and passengers are homogeneous. All drivers are equally competitive and are the same to all passengers. In addition, all drivers earn the same amount from the same passenger trip as all taxis use the government regulated fare structure; this fare structure is common knowledge to all passengers. Drivers are not rated by passengers, and passengers have no information to discriminate against any taxi for any trip. Second, only drivers decide whether or not to enter the market. Demand is passive as passengers wait at their locations and indicate their intention to hire when taxis approach. Drivers are rewarded for choosing the market that offers a better chance of getting a passenger quickly with a higher expected trip length, and hence effectively earning a higher "wage rate."

However, there are also two major differences between taxi markets and market-entry games in the lab. First, as opposed to typical market-entry games where market sizes are announced and are common knowledge, it may not be true that all drivers have sufficient and relevant knowledge about all markets. Having sufficient and relevant knowledge about taxi markets means that a driver knows the average search time for a passenger and the average trip length for each market. These two pieces of information together determine the expected payoff of a market at a particular time. Second, drivers make a sequence of path-dependent entry decisions but have no say where they make the next decision as the passenger decides the drop off location. Therefore, commonly available trip-level data will not accurately capture the decision parameters facing a driver at each decision point, and it is also important to know the movement path of a taxi when the taxi is searching for a passenger. Our data consists of the location of a taxi at 15-second intervals. During these intervals, we also know whether the taxi was available for hire. This information allows us to identify decision points.

Previous studies of the taxi market, such as Lagos (2003), Buchholz (2019) and Frechette et al. (2019), relied on trip-level data to analyse spatial search but such data had no information about the location of the taxis when the taxis were idle. These researchers assumed drivers always chose the optimal entry decision, then calibrated a general equilibrium model based on this assumption.[1] Our dataset fills the research gap using a 15-second data feed. This feed shows individual taxi location as well as the taxi's status (for hire or not-for-hire) during each time interval. Using the movement of vacant taxis and comparing the profitability of locations, we examine how close taxi drivers are to choosing the optimal market. Overall, the location- and time-specific data for each taxi in our sample allow us to quantify the deviation of individual drivers from their theoretical optimal path.

Taxi markets in Singapore also offer two modeling advantages. First, the city state is a small island. Hence the markets have a natural and clear geographical boundary, which results in fewer concerns about the entry and exit of taxis and passengers from elsewhere. Second, where and when a driver starts and stops work during each shift is fixed for most drivers. Without the need to decide where and when to stop work, the daily decision-making tasks of a driver reduce to just market entry decisions.

We model the entry decisions at 5-minute intervals whenever a taxi is available for hire. In particular, the moment a taxi is available for hire after the last drop-off is defined to be a decision point, and thereafter every 5 minutes the taxi remains empty is also a decision point. Using the 5-minute interval to define a decision point is reasonable because 5 to 10 minutes is all a taxi takes to travel across two neighbouring markets. We also define the location of the taxi at a certain point to be the market choice of the last entry decision.

Our empirical investigation proceeds in two stages. First, we check for disequilibrium by verifying whether there is an arbitrage opportunity between two markets. An arbitrage opportunity exists if the difference in wage rates between two markets is more than the travel cost (friction). Drivers would have an incentive to incur the travel cost to move from the low-wage-rate market to the high one and make a profit.[2] Markets are not in equilibrium if such arbitrage exists.[3]

[1]Other related papers examine workers' ability to play the optimal strategy among professional athletes. See Chiappori et al. (2002), Palacios-Huerta (2003), Romer (2006), Hall et al. (2017) and Chen et al. (2017).

[2]We assume that the markets do not differ in dis-incentive caused by non-monetary features of a market.

[3]We find such arbitrage does exist. For example, hourly wage rate was \$8.77 in district 6 in June as reported in Table A2 and wage rate in the neighboring 4 districts (4,5,7,8) ranged from \$3.79 to \$6.12; while travel costs from these districts to district 6 were no more than \$2.

Second, we estimate the earning loss for each decision and find key factors that explain why some decisions fare better than others. Specifically, we find that market knowledge explains an additional 3% variation of the earning losses in the 2.6 million decisions, a 74% improvement in model fit, establishing the necessary condition for coordination for market entry in the field. On the other hand, strategic thinking and risk preference does not have any significant impact on earning loss. In fact, more than 85% of the decisions made are non-strategic; there is no incentive to be strategic as there is little risk of over-entry in the better-paying markets. In summary, we hope to add to the understanding of the drivers' suboptimal decisions, and to use this information to inform interventions that will increase earnings and improve social welfare, see Cramer and Krueger (2016).

The rest of this paper is structured as follows. Section 2 describes the data and Section 3 provides comments on driver behaviors. Section 4 presents empirical evidence on the disequilibrium. Section 5 lays out a dynamic programming model for a driver's optimal decision, and Section 6 presents the empirical evidence for the driver's deviation from the optimal solution, quantifies earning loss, and describes factors that mitigate the loss. Finally, Section 7 concludes.

2 Data

The data contains the locations and statuses of 2,728 taxis at 15-second intervals over a three-month period, from April to June 2014, in Singapore. The data covers a total of 146,071 work shifts worked by the 2,728 taxi drivers and contains a total of 588,764 GPS location points. The taxis used in this study represented approximately 10% of all taxis in the city.[4] An in-vehicle console, acting as a control panel for the taxi driver, captured both the location (via GPS) and status (on break, looking for a passenger, passenger on board) of the taxi. The information was transmitted to the taxi company roughly every 15 seconds. The transmission ended when a driver signed out of the console at the end of the work shift. This data is augmented with driver-specific information about driver demographics, income, and employment history obtained from the taxi company. Panels A and B of Table 1 list the summary statistics of the driver demographics, daily earnings, and vehicle status.

We reduced the unnecessary granularity of the original data via two methods. First, as we were interested in taxi drivers' search behavior, we only kept the location and time data for the origin and destination of a passenger trip, and removed the location data

[4]These 2,728 taxis belonged to the same company, were of similar models and were driven by drivers who were recruited and trained under the same system. The drivers received the same services such as maintenance, insurance, and call booking from the company.

between the two ends of each trip. We did the same for breaks taken by the drivers as well. Second, we needed to define markets of a reasonable size to perform a meaningful analysis. The 720 square kilometers of Singapore are divided into 28 districts for city-planning purposes, and the population density in each district does not vary too drastically from that of the others. In addition, the airport is a unique and interesting location with a non-local source of passengers that forms a market of its own. Hence, we found it reasonable to use the district system together with the airport to create 29 markets for our analysis. As it takes between 5 and 10 minutes to drive from a district to a neighboring district, it was sufficient that we aggregated the times when a taxi was searching for passengers into 5-minute intervals and used the ending district to represent its location during each 5 minutes. This market division is comparable to that in Frechette et al. (2019) and Buchholz (2019).

Formally, we define a market as a district d in a 5-minute interval t. The demand arising from each market is defined by three parameters: the (expected) number of trips originating in the district in the 5-minute interval, a 29 by 29 transition matrix that records the proportion of the trips going from each district to the 29 districts (including the trips within districts), and a vector of the average lengths (in minutes) of trips to each of the 29 districts. These parameters largely capture any locational characteristics relevant to the expected revenue from the respective markets. Operationally, we averaged the number of pick-ups in each district for each 5-minute interval (288 intervals in a day) across 91 days. We computed the vectors of average trip lengths and vectors of trip proportions for the 29 markets using a 30-minute window separately for weekdays and weekends. We used the 30-minute window for these vectors because the data would have been too sparse if we had used a 5-minute window. The 30-minute window still offered a reasonable approximation of varying demand conditions due to traffic and peak periods. We divided the number of pick-ups by the total number of taxis in the market to produce a pick-up rate. Table A1 summarizes the average trip length and the pick-up rate for each market. The average pick-up rates across markets range from 8% to 35%, and the market average trip-time ranges from 12 to 21 minutes.

We calculate taxi fares at the individual-trip level by using the GPS driving records and validate our calculation with the daily total earnings data collected by the company. To do so, we translated all the expected trip times into dollar values by using the advertised trip-fare formula. We assumed the average driving speed was 50 km/h and used a driving-time formula of 36 cents per 45 seconds, then added a base fixed fare of S$3.2. If the starting district was the airport, a base S$3 surcharge was added; if the starting district was the airport, on Friday, Saturday or Sunday, between 17:00 and 00:00, an additional S$2 was added. For weekdays (Monday through Friday) between 06:00 and

09:30, the dollar value was increased by 25%; for all days from 18:00 to 00:00, the dollar value was increased by 25%; for all days from 00:00 to 06:00, the dollar value was increased by 50%.

Although our analysis was based on a randomly drawn a sample of 10% of the taxis in the market, we verified the representativeness of this 2014 sample using the trip level data of the entire taxi population for the period of April to June 2015. The trip-level data consists of fare, origin market, destination market, departure time, and arrival time for each trip. The data covers the entire taxi population of Singapore, but we do not have the 15-second location and status data to model the search path of an empty taxi. Using this 2015 trip-level data, we tested the hypotheses that the proportion of trips in each market and the corresponding trip lengths in our sample were no different from the population. The Kolmogorov-Smirnov distribution tests (p value > 0.2) suggested that we could not reject the hypothesis that the sample statistics are no different from the population statistics. The detailed results are provided in the Figure A1 in the appendix.

3 Driver Behavior

Taxi drivers make two types of decisions in their daily work shift: their working hours and the locations they search after passenger drop-offs. Previous studies of taxi-driver labor supply, such as Camerer et al. (1997), Crawford and Meng (2011), Farber (2008), and Thakral and Tô (Forthcoming), discussed whether taxi drivers were more likely to end shifts earlier if they achieved their target incomes. However, a large proportion of taxi drivers have a fixed work schedule in Singapore, so only search decisions are relevant to most drivers in Singapore.

To generate supporting evidence using our data, we plot the distribution of deviation from the personal average starting and ending times for taxi drivers in the left panel of Figure 1. After excluding the drivers who switched between morning and night shifts (4% of the total number), we find that 78.2% of taxi shifts started within an hour of the driver's average starting time, and 70.6% of shifts ended within an hour of the drivers' average ending time. This finding is not surprising because about 60% of taxis are two-shift taxis, with a day-time regular driver who passes the taxi to a relief driver for the night shift at a pre-arranged time and location. We further split the left panel of Figure 1 into the regular drivers (Figure A2) and relief drivers (Figure A3). Deviations in both figures are similar to those in Figure 1.

Almost all the drivers in our data also kept the same starting and ending locations in most, if not all, of their work shifts. We plot drivers' starting and ending locations in the right panel of Figure 1, and confirm that almost all drivers returned the taxis to the locations from which they started their shifts. Hence, it is reasonable to assume that both the times and locations to start and end a shift are known by the driver ahead of the shift.

4 Arbitrage Opportunity

The expected hourly wage rates at every hour for any two districts should be quite similar in equilibrium.[5] Any significant difference between an arbitrary pair of districts beyond the friction cost of traveling between the pair, namely the amount of time and fuel cost for a taxi in the lower-wage-rate district to move to the higher-wage-rate district would present an arbitrage opportunity. If such arbitrage opportunities are present, then the markets are likely in disequilibrium assuming all drivers are income maximizing. We show in reduced form below that such arbitrage opportunities were present in our data.

To estimate the hourly wage rate of each district, we regress the daily earnings of a driver on the amount of work time the driver spent in each district in each hour of the shift. Let Y_{is} denotes the earnings of driver i in shift s, and T_{isd} denote the amount of work time (in a fraction of an hour) that driver i spent during shift s in district d ($d = \{1, 2, \cdots, 29\}$). There are a total of 29 work-time variables. Work time is defined as the time spent searching for passengers (FREE) and the time with a passenger on board (POB). We attribute the entire POB time to the district the trip originated from. Figure 2 shows that a typical driver spent more than 40% of their work time searching for a passenger in any given hour.[6]

Formally, the regression is as follows:

$$Y_{is} = \beta_d' T_{isd} + \delta' D_{is} + \epsilon_{is},$$

where D_{is} accounts for the fixed effects due to driver i (such as the driver's age and driving experience) and the fixed effects due to shift s (such as day of the week); ϵ_{is} is the remaining random error assumed to be i.i.d. over i and s.

[5] We assume that all drivers only care about maximizing their hourly wage rate. There might be preference for non-monetary payoffs where some drivers may have preferences for certain district characteristics. As long as these preferences are driver-specific and randomly distributed across drivers, this statement about equilibrium is still valid as there will still be drivers who arbitrage.

[6] We calculate the taxi-search-time fraction of each hour using search time divided by total active work time (in "POB" or "FREE" status). To show how passenger trips are distributed geographically, we show the number of drop-offs and pick-ups by districts in Figure A4.

The corresponding regression coefficients β_d approximate the marginal hourly wage rates in district d. With 2,728 drivers each working 78 shifts in the 91 days, we have 220,056 rows of data to estimate the 29 marginal hourly wage rates. We plot the average regression coefficients β_d by district in Figure 3.[7] The conservatively estimated difference between the highest and lowest rates is S$6.1 per hour (S$8.2 - S$2.1). For an eight-hour shift, this comes to at least S$48.8.

In addition to estimating the regression on all 91 days, we also estimate three separate regressions for the three months. The detailed results are included in Table A2 in the appendix. There was no reduction in differences across markets and the marginal wage rates across the months for the same market remained similar. We repeated the analysis separately for both regular and relief drivers; the estimates are reported in Table A3. While the higher wage rates for relief drivers reflected a 50% late-night surcharge for the night shift, the differences across markets were there and remain across the three months for both driver types.

These reduced-form results suggested that the markets are not in equilibrium nor is there any sign of convergence. Contrary to common assumptions in prior literature about spatial competition in the taxi market (e.g. Buchholz, 2019), we do not think drivers, in general, follow optimal search routes throughout their work shifts. We believe the markets were in disequilibrium because drivers failed to optimize some of their search decisions. Our data contains the detailed dynamic search decision of each driver to allow us to check our conjecture. We model the dynamic search sequences of the drivers, derive the optimal search decisions, and compute the loss in earnings if the actual decisions are suboptimal.

5 Optimal Entry Decisions

We find optimal solutions to all entry decisions and contrast them with the actual decisions by the drivers to find the exact arbitrage opportunities. Each entry decision would have an impact on all subsequent decisions for a shift. Hence, finding the optimal entry decision requires finding optimal market entries for subsequent decisions as well. Due to this recursive nature of optimal decision, we use dynamic programming to solve for the optimal entries for the entire decision sequence for a shift. We develop the formula below.

[7] We have also estimated the marginal hourly wage rates at 3-hour intervals. In other words, we defined the independent variables T_{istd} where $t = 1, ..., 8$ indicating the eight 3-hour intervals, generating a total of 232 β_{td} (29 districts by 8 intervals). Figure A5 plots the marginal hourly wage rates for the eight intervals.

Assuming fixed ending locations and end-times for the daily shifts of each driver, we model the daily search decisions of the driver with two indices, time period t and market d. Suppose the daily shift of a driver is broken down into T discrete periods, which are 5-minute intervals in our empirical analysis. Without loss of generality, we set the first 5-minute interval of all drivers to be the first 5 minutes starting from midnight such that $t \in \{1, 2, \cdots, 288\}$.

In each time period t, a working driver i can face one of the two passenger states: **FREE** to pick up a passenger (passenger state = 0) or **passenger on board, POB** (passenger state = 1). We define the cumulative values for the respective states as $V_i^0(t, d)$ and $V_i^1(t, d)$. If the driver faces passenger state = 0, he faces a decision about which market to go to. The expected value of going to market d' from market d is the weighted values of the two states that the driver will face in market d' as follows:

$$W_i(t, d, d') = \sigma(t', d')V_i^1(t', d') + (1 - \sigma(t', d'))V_i^0(t', d'),$$

where

- $t' = t + \lambda(t, d, d')$ is the time period that a driver arriving in market d' starts in t from market d.

- $\sigma(t, d)$ is the likelihood that a taxi picks up a passenger in district d in period t which is estimated in 5-minute windows every day in every district.[8]

- $\lambda(t, d, d")$ is the average trip time from district d to district $d"$ in period t. Two sets of trip-time matrices are computed using 30-minute windows, one for weekdays and one for weekends. We assume the same trip time for each 5-minute period within a 30-minute window.

With the expected values $W_i(t, d, d')$ for all d', the driver i chooses the market that gives the highest value and this maximum is the value of passenger state = 0, where the decision is made. Formally,

$$V_i^0(t, d) = max_{d' \in \Delta_{it}}\{W_i(t, d, d'), \forall d' \in \{1, 2, \cdots, 29\}\},$$

where Δ_{it} is the set of markets that include the ending location and ending time of driver i as a feasible end point. In other words, the set contains all markets that can reach the

[8] Although the pick-up rate is endogenous to entry decisions, a driver's individual entry decision would have no significant impact on the denominator of the pick-up rate, because there are close to 30,000 taxis in Singapore, or an average of about 1000 taxis per district.

ending location D by ending time T, $\Delta_{it} = \{d' : t' + \lambda(t', d', D) \leq T\}$.

The expected value for the state of "passenger on board" consists of two components. The first component is the value generated from the passenger trip itself and the second is the expected value of going to the destination market d'.[9] Summing all possible destination markets, the total expected value can be found using:

$$V_i^1(t, d) = \{\sum_{d' \in \Delta_{it}} \theta(t, d, d')[\psi_{td} + \phi_{td}\lambda(t, d, d') + W_i(t', d, d')]\},$$

where

- $\theta(t, d, d')$ is the proportion of trips transiting from district d to district d' in period t. Similar assumptions to those for $\lambda(t, d, d")$ are used for the computation of the transition matrices for weekdays and weekends.

- ψ_{td} is the fixed component and ϕ_{td} is the variable component of the fare structure. Every trip starts with a fixed fee of \$3.2 but some charges may be specific to a particular time (such as the peak-hour rate) or a particular location (such as the fixed airport surcharge) or both.

Using the above dynamic programming structure, we can determine a driver's optimal search decision at every search point through backward induction. The value functions of market d for both states in the last period are

$$V_i^1(T, d) = \{\sum_{d' \in \Delta_{iT}} \theta(T, d, d')[\psi_{Td} + \phi_{Td}\lambda(T, d, d')]\},$$

and $V_i^0(T, d) = 0$. The value functions for prior periods can then be recursively backed out.

Using the dynamic programming formulation above, we solved the optimal decision at every decision point for all shifts. To provide a glimpse of how actual choices deviated from optimal decisions, we mapped out the dyads, (chosen market, optimal market), for three different relatively more busy time periods: 7 - 9 a.m., 12 - 2 p.m. and 5 - 7 p.m.[10] The plots are in Figure 4. The off-diagonal bubbles are the suboptimal entry decisions. Some districts seemed to persistently attract too many drivers as shown in the big bubbles in the lower diagonal section of Figure 4.[11] We explore the factors that drove these

[9]We do not include fuel cost into the calculation as the car engine is always running regardless of passenger state in Singapore.

[10]Plots for the remaining time periods can be requested from the authors.

[11]Focusing on market 29 (where Changi airport is located), we observed large concentrations of both off-diagonal horizontal (where optimal market was 29 but not chosen) and vertical strings of bubbles

decisions next.

6 Earning Loss

We define the earning loss of a decision by driver i in period t and district d, $L_i(t,d)$. It is the value of the best decision i could make minus the value of the decision i actually makes, as follows:

$$L_i(t,d) = V_i^0(t,d) - W_i(t,d,d_i)$$

where d_i is the actual choice of driver i.

Table 1 lists the summary statistics comparing the driver's working patterns and daily income. The average age of drivers was 54.7 and, on average, they had been with their respective taxi companies for 2.4 years. The average daily income (gross revenue from taxi fare) was S\$201.40. Consistent with the anecdotal evidence that a large proportion of taxi drivers had a fixed working schedule, we indeed found that 63% of drivers in our sample were relief drivers who took night shifts. Each shift lasted 456 minutes on average and of those 456 minutes, drivers spent an average of 135 minutes actively searching for a passenger. We then listed the model-predicted optimum income and loss per shift for each type of driver. If a driver followed the optimal search path for the entire shift, we classified the potential maximum earning of that shift as an optimal earning. Each driver on average lost S\$46 in a shift, which accounted for 17% of their potential income and 22% of their actual income. Regular and relief drivers had similar optimal earnings and aggregated earning losses per shift (see Panel C of Table 1); both regular and relief drivers achieved only about 80% of their potential income.

In Table 2, we focus on earning loss at the individual decision level. We find that only 32% of the 3,930,884 location decisions are optimal. If we define the close-to-optimal search decisions as those with earning losses smaller than S\$0.10, still only 34% of decisions were close to optimality. If we consider S\$1 per decision as economically significant, nearly 50% of search decisions generate significant earning losses. The average earning loss per decision is S\$1.69, which is consistent with the shift-level loss calculated in Table

(where market 29 was chosen but not optimal) in Figure 4. Ho et al. (2020) offered an explanation for such phenomenon. Working on the same dataset, they found that not enough drivers were staying after dropping off passengers at the airport and many drivers who went empty left empty; trips from the airport were longer but not taken into account by drivers who cared about the long taxi queue. Both are the reasons why we observe the off-diagonal horizontal and vertical strings of bubbles for market 29 in Figure 4. Drivers who did not stay at the airport on average earned S\$4.40 less than those who stayed.

1.

The standard deviation in the daily earning loss across drivers is large, at S$33 (see Table 1), which suggests a large variation in earning loss among drivers. Why are some drivers better than others at choosing the right markets to enter? We investigate three obvious possibilities. First, the lack of market knowledge may hinder optimal decision making because market knowledge provides the key parameters into the entry decisions for a driver. Second, the drivers might not be strategically minded or otherwise able to take into account other drivers' entry decisions. Third, drivers might exhibit non-monetary preferences such as preference towards local trips or aversions to risky markets nearby; this could potentially dampen the drivers' incentives to chase for better wage rates in the other markets.

We empirically test the impact of these three driver-specific characteristics (market knowledge, strategic thinking and market preference) through the use of the following regression:

$$L_i(t, d) = \gamma Z_i + \zeta X_{it} + \delta D_{td} + \epsilon_{itd}, \tag{1}$$

where Z_i represents aforementioned driver-specific characteristics, X_{it} (e.g. cumulative working time), D_{td} accounts for district and time specific market conditions (such as the pick-up probability and number of phone bookings) and the fixed effects due to time of the decision t (such as day of the week and drivers' starting hours); ϵ_{itd} is the remaining random error assumed to be i.i.d. We also apply the regression model to regular drivers and relief drivers separately.

We construct proxy measures from the driving behaviors of the drivers for the regression analysis. We include two proxy measures for X_{it}. As a measure of fatigue, we use cumulative work-time up to the decision point. Fatigue is more likely to set in when the driver drives for a longer time; this will likely lead to more suboptimal decisions and greater earning losses. Thus, we expect the coefficient to be positive. We include the cumulative earnings up to the decision point to test the target income hypothesis. In particular, higher cumulative earnings lead to lower motivation to make optimal decisions; so we expect the coefficient to be positive.[12]

[12]Target income hypotheses from earlier literature suggested that a driver stopped work when he reached his target income. We did not observe a high variation in stopping time as we noted in Figure 1, so stopping time would not be a good dependent variable to test the target income hypothesis. We believe if there is a target-income effect, it will manifest in lower motivation to search for passengers optimally.

6.1 Market Knowledge

Market experience and knowledge improve productivity (see Haggag et al., 2017) and remove anomalies (see List, 2003). In particular, Haggag et al. (2017) found taxi drivers' productivity improved by accumulating neighborhood-specific experience. We use the "familiarity of a market" as a proxy for the market knowledge and define the familiarity of a market as the proportion of working time a driver spent in each market in April. On the other hand, the work experience of a driver, as indicated by the number of years being a taxi driver, might not offer a good measure of market knowledge because of the constantly evolving nature of cities. For instance, new subway lines, new offices, and new shopping centers may be built. However, we still include the work experience variable as a control. For each decision, we include two knowledge measures, the driver's "familiarity with the optimal market(s)" and "familiarity with the present market(s)" at the decision point. We expect a higher familiarity leads to a lower loss of earnings for the decision concerned. Thus, we expect both measures to have a negative coefficient.

Two driver behaviors that are unique to the Singapore taxi markets might affect the entry decisions of a driver. We discuss both in this subsection because they may potentially be proxies for market knowledge. We include them in the model but do not attribute their model-fit contribution to market knowledge. First, some drivers prefer running short trips. These trips are usually the last-mile trips such as the subway-to-home trips and the local-market-to-home trips that happen in the residential districts. We construct a measure for this "short trip preference." Specifically, we define it to be the percentage of work-time a driver spent in the 14 short-trip-generating markets.[13] This captures not only the preference but also the knowledge a driver may have that comes from serving the markets with higher demand for short trips. Hence, one can argue that it is a proxy for market knowledge as well; and we expect the coefficient to be negative as better knowledge leads to less loss.

Second, most taxi drivers typically hang out with other buddy drivers for lunch at their usual joints. Anecdotally, they share market information during these lunch breaks, and so drivers may be more knowledgeable about some markets after their lunch breaks. We define an indicator variable that indicates whether the decision is before a break. Based on this, we expect the coefficient to be positive because decisions before a break are more likely to lead to a loss.

[13]We compute the average trip length originating from each market using data from the month of April, rank the average trip lengths, and label the 14 shortest districts (out of 29 total) as short-trip markets.

6.2 Strategic Thinking

Taking competition into account is important in making better decisions. The neglect of competition led to crowded markets, e.g. Moore et al. (2007), Simonsohn (2010). The presence of strategic thinking (Crawford et al., 2013) or strategic intelligence (Levine et al., 2017) was significant in explaining better market entry decisions (e.g. Goldfarb and Yang, 2009, Goldfarb and Xiao, 2011) and better business decisions in general (e.g. Hortaçsu et al., 2019, DellaVigna and Gentzkow, 2019). These decisions are high stakes, infrequent, and have the luxury of time for a careful evaluation. For the taxi drivers, decisions are low stakes, frequent, and need to be made on the go. Nevertheless, the effort to engage in strategic thinking may be important in explaining the decisions of some taxi drivers. Similar to previous studies of market entry decisions, we organize the different levels of efforts using the cognitive hierarchy framework as in Camerer et al. (2004).

For the remainder of this subsection, we describe how the strategic effort level of each driver is determined from the data and how proxy measures for strategic thinking of a driver are derived. Conceptually, a level-0 driver exerts minimal effort by randomizing across all feasible markets. A level-1 driver chooses the market with the best payoff, assuming all other drivers accessing the same set of markets to be level-0. In general, a level-k driver best responds assuming others to be lower than level-k.

When considering which market to enter, a level-k driver ($k \geq 1$) considers two quantities associated with each market d in period t: the expected number of trips originating from market d in period t, $N(t,d)$; and the expected fare for a trip originating from market d in period t, $F(t,d)$. $N(t,d)$ is estimated by averaging the number of trips originating from the market d for a 5-minute interval t using all 91 days in the data set. Using the parameters of the trip time from d to d' ($\lambda(t,d,d')$), the fixed and variable components of the fare (ψ_{td}, ϕ_{td}), and weighted by the proportion of trips transiting from d to d' ($\theta(t,d,d')$), we form the expected fare from choosing market d in period t[14]:

$$F_1(t,d) = \{\sum_{d'} \theta(t,d,d')[\psi_{td} + \phi_{td}\lambda(t,d,d')]\}.$$

More importantly, the level-k driver would consider how many other drivers (of lower levels) choose to enter each market which is embodied in the probability of getting a ride. Let $E_k(t,d')$ be the probability for level-k to get a ride in the market d' in period t after taking into account the entry decisions of lower levels. Using the square bracket

[14]We use F_1 to denote the mean fare and F_2 to denote the variance.

notation $[d]$ to indicate the driver's location in market d when making decision in period t, a level-k driver located in market $[d]$ chooses to enter the market $D_k(t,[d])$ in period t if it gives the best expected fare. Formally,

$$D_k(t,[d]) = argmax_{d' \in \Delta_{[d]}}\{F_1(t,d') \cdot E_k(t,d')\},$$

where

- $E_k(t,d')$ is computed using the estimated number of trips and the entry decisions of level $k-1$ and below. More specifically, $E_k(t,d') = min\{\frac{N(t,d')}{S_{k-1}(t,d')}, 1\}$.
- $S_{k-1}(t,d')$ is the cumulative number of drivers (level $k-1$ and below) who choose to enter market d' in the period t.
- $\Delta_{[d]} = \{d'$: the neighbouring markets to market $[d],[d]$ inclusive$\}$ is the set of all markets that are adjacent to market $[d]$ where the driver is located. In the data, we find that over 96% of entry decisions are indeed made in $\Delta_{[d]}$ as drivers largely look for passengers in the adjacent areas. Some non-adjacent markets are not reachable within 5 minutes while other markets may have noticeably high friction costs that even level-0 drivers would not consider (minimum aversion of level-0 as noted in Chong et al. (2016)).

And the cumulative number of drivers up to level k selecting market d in period t is derived as follows:

$$S_k(t,d) = \Sigma_{l=0}^{k-1}\pi_l \sum_{[d']}\{I[D_l(t,[d']) = d; d \in \Delta_{[d']}] \cdot M(t,[d'])\},$$

where the number of level-k drivers choosing market d are aggregated across the markets $[d']$ they are located at; and

- π_l is the proportion of drivers with level-l effort. We use a Poisson distribution with a mean of τ to approximate the distribution of effort level.
- I[condition] is an indicator function for the condition.
- $M(t,[d])$ is the number of drivers located at market $[d]$ in period t. $M(t,d)$ is estimated by averaging the number of drivers with passengers on board and those searching for passengers in the market d for a 5-minute interval t using all 91 days in the data set.
- The cumulative number of level-0 drivers, $S_0(t,d) = \pi_0 \sum_{[d']} \frac{1}{|\Delta_{[d']}|} M(t,[d'])$ for $d \in \Delta_{[d']}$. The level-0 drivers located in market $[d']$ randomize over all markets in $\Delta_{[d']}$.

We derive two proxy measures of strategic efforts for each driver, share of level-0 decisions and share of level ≥ 1 decisions, to capture the non-strategic and strategic proportions of the driver decisions. We determine the effort level for the 3,930,884 decisions by comparing them to the level-k decisions (i.e. $D_k(t, [d])$). If a search decision is only consistent with level-0 thinking, we classify it as a level-0 decision. If a decision is consistent with both level-0 and level-1, we classify it as level-1, and similarly for all level $k \geq 2$ decisions. For decisions consistent with level-k and above, we classify these decisions as level $\geq k$.

We start with the Poisson mean $\tau = 1.5$ to classify the entry decisions and find that close to 85% of the decisions are level-0 decisions. We then revise the mean to $\tau = 0.165$ so that it better reflects the high percentage of level-0 decisions. The results of the classification for both $\tau = 1.50$ and $\tau = 0.165$ are reported in Panel A of Table 3. Strategic thinking is not common as no more than 11% of the decisions are level ≥ 1 decisions. Less than 4% of the decisions are non-adjacent markets not covered by the model and hence are not classified. We categorize the decisions of a driver into three clusters: level-0, level ≥ 1 , not classified; shares of decisions are then computed. Consistent with our knowledge measures, we use all decisions made by a driver in April to compute the value of two proxy measures. These form the second group of driver-specific characteristics Z_i in Equation 1.

6.3 Risk Preference

Some drivers may be averse to risky markets and opt to minimize fluctuations in earnings over time rather than to maximize their expected income. We considered two possible risk-minimizing decision rules: 1) choose the market that has the least (mean-adjusted) variance in earnings and 2) choose the market with the highest pick-up probability. We compute the shares of decisions made by a driver using these rules and use them as proxy measures for the risk preference of the driver. We provide the details of these computations in the remainder of this subsection.

We formalize the two decision rules as follows. Let $F_2(t, d)$ be the variance of fare for trips originating from market d in period t, where $F_1(t, d)$ is mean fare. The decision that follows the minimum mean-adjusted variance rule is:

$$D_r(t, [d]) = argmin_{d' \in \Delta_{[d]}} \{\frac{F_2(t, d')}{F_1(t, d')}\};$$

and the decision that follows the highest pick-up probability rule is:

$$D_p(t, [d]) = argmax_{d' \in \Delta_{[d]}}\{E(t, d')\}.$$

We derive two proxy measures of risk preference for each driver: share of variance-minimizing decisions and share of pick-up-probability-maximizing decisions. For each decision, we compute the mean-adjusted earning variance and the pick-up probability for all adjacent markets where the driver was located. We count the decisions that coincided with the minimum of the mean-adjusted earning variance and the maximum of the pick-up probability and compute the respective decision shares. The result of this classification exercise is reported in Panel B of Table 3. We do not find the drivers to be very risk averse as only 14.9% of decisions are the minimum mean-adjusted earning variance and 24.3% of decisions are the maximum pick-up probability. Consistent with the knowledge and strategic effort measures in the last two subsections, we use all decisions made by a driver in April to compute the value of the two proxy measures. These form the third group of driver-specific characteristics Z_i in our regression specification of Equation 1.

6.4 Empirical Results

We regress Equation 1 using data from May to June while using the April data to estimate the driver-specific characteristics proxy measures on market knowledge, strategic thinking and risk preference. Table 4 reports the estimation results for all drivers and for regular and relief drivers separately. Details of the coefficients for the driver-specific characteristics Z_i and for a driver's continuous status throughout a shift (cumulative earnings and cumulative working time up to a decision point) X_{it} are reported at the significance level of $p < 0.01$.

Cumulative-working-time is positively significant, suggesting fatigue is likely to be a cause for suboptimal decisions, especially for relief drivers working night shift. Contrary to our target income prediction, cumulative-earnings is significant at -0.0444 for all drivers, which was equivalent to a S$0.044 decrease in loss as a driver doubles her accumulated earnings in a daily shift. The effect, though small in magnitude, differs by driver shift-type; the marginal effect of cumulative earning is -0.0269 for regular drivers and doubles at -0.0541 for relief drivers. This result suggests that when a driver has higher earnings up to the decision point, she is less likely to make a suboptimal decision.

Familiarity with optimal-markets is significant at -4.1309, which means that a driver's earning loss would decrease by S$0.413 if a driver was 10% more familiar with the optimal district, which would account for a 24% reduction in average earning loss. Compared to the coefficient (-0.6112) for familiarity-with-current-market, familiarity-with-optimal-market is 6 times more impactful. Short-trip-preference is also significant with the expected sign at -0.6026, indicating that a driver's earning loss would be S$0.060 lower if she preferred to have 10% more short trips. Decision-before-a-break is positively significant at 0.0327 overall. It is significant at 0.0621 for the regular drivers, suggesting that the search decisions made before a break were likely to cost a driver more in earnings compared to other decisions. However, it is insignificant for relief drivers, which is consistent with the fact that many relief drivers might be driving the night shifts and hence were less likely to have coordinated breaks.

The coefficients for both level-0 share and level ≥ 1 share are significantly negative, although not significantly different from each other. This result highlights the difference in earning loss between adjacent markets and non-adjacent markets, but not between strategic and non-strategic decisions. Given that most decisions are level-0, a consistent hypothesis is that it does not pay to be strategic and hence most drivers remained non-strategic. Finally, risk preference does not explain the earning loss as both proxy measures for risk preference are not statistically significant.

We find that earning loss could be explained by (a lack of) market knowledge but not by (a lack of) strategic thinking nor by risk preference. Overall, the inclusion of driver-specific characteristics to the baseline model explains an additional 3.54 percentage points of the variation in earning loss, increasing from 4.49% to 8.03% to produce a 78.8% improvement. The addition of the market knowledge measures alone increase the regression fit from 4.49% by 3.32 percentage points to 7.81%, improving the fit by 73.9% for more than 2.6 million decisions in the months of May and June.[15] The addition of strategic thinking and risk preference measures improve fit by 0.27 percentage points (driven mainly by the classification of non-adjacent market choices), a 6% improvement over the baseline model.[16]

7 Conclusion

Unlike the consistent equilibrium outcomes for market-entry games in the lab, field evidence from the taxi markets in Singapore reveals significant disequilibrium. This disequilibrium manifests itself in gaps among marginal wage rates across the markets. These differences in the marginal wage rate reflect the imbalances in taxi supply across the markets that result from suboptimal market entry decisions by some drivers.

[15] Detailed estimation result including market knowledge is reported in the appendix Table A4.

[16] Detailed estimation result including strategic thinking and risk preference is reported in the appendix Table A5

We investigate three possible reasons for the suboptimal decisions: insufficient knowledge about the markets, insufficient attention to competition and idiosyncratic preferences for some markets. The earning losses are reduced if the drivers are familiar with the relevant markets at a decision point; strategic thinking and risk preference have no effect. Market knowledge explained an additional 3% of the variation in earning losses for the 2.6 million decisions, resulting in a 73.9% improvement in fit.

Our analysis points to the lack of market knowledge of individual drivers as an important cause for the suboptimal decisions that led to the existence of arbitrage opportunities. Our empirical results suggest that the drivers did learn from their own past experience, and they were able to use the limited market knowledge learned, where and when it was relevant, to avoid earning losses. Most drivers were not strategic in their decisions and being strategic did not reduce earning loss, but simply avoiding non-adjacent markets did. Avoiding risky markets or choosing safe markets neither increased nor decreased earning loss. In summary, our work empirically validates that market knowledge is a crucial first step toward realizing the magic of coordination in the taxi markets.

We envision that as more and more drivers take advantage of the arbitrage opportunities by making optimal entry decisions while upgrading and updating their market knowledge, the magic of coordination will emerge when market knowledge stabilizes and arbitrage opportunities are competed away.[17] And it is perhaps only then that the drivers would become strategic because the likelihood of over-entry in some markets increases. To validate this equilibration process convincingly requires a larger dataset in a stable market environment (both conditions are currently luxury). Alternatively, a centralized booking system for all drivers may also achieve the coordination function, removing the need for market knowledge and strategic thinking, and reducing the earning fluctuation.

[17]The pickup probabilities are endogenous. As drivers optimize and change their entry decisions, pickup probabilities will correspondingly change leading to changes in optimal entries; this is when strategic thinking becomes important. And the cycle continues until the equilibrium is achieved.

Table 1: Taxi Drivers and Vehicle Status, Actual and Counter-factual Income

	(1) N	(2) Mean	(3) S.D.
Panel A	Drivers' demographics		
Age (in years)	2,728	54.7	8.57
Work experience (in years)	2,728	2.42	2.50
Income (S$ per day)	146,071	201.41	87.42
Relief driver proportion	2,728	0.63	0.48
Panel B	Vehicle status		
Total work time (minutes)	146,071	456	208
Search time (minutes)	146,071	135	86
Break time (minutes)	146,071	75	95
Passenger on board (minutes)	146,071	246	140
Panel C	Per shift		
All Driver			
Daily loss in income (S$ per day)	128,957	46.16	33.01
Optimum income (S$ per day)	128,957	268.79	108.67
Number of search decisions	128,957	46.00	28.56
Regular Driver			
Daily loss in income (S$ per day)	55,785	43.84	31.86
Optimum income (S$ per day)	55,785	263.34	108.38
Number of search decisions	55,785	42.89	26.24
Relief Driver			
Daily loss in income (S$ per day)	73,172	47.92	33.76
Optimum income (S$ per day)	73,172	272.92	108.42
Number of search decisions	73,172	48.38	29.99

Note: All earnings and losses are measured in Singapore dollars and time related variables are measured in minutes. Vehicle status data include all driving records. Shift level summary statistics include all day and night shifts and exclude shifts with irregular lengths.

Table 2: Optimal Proportion and Earning Loss per Search Decision

	(1) N	(2) Mean
All Driver		
Loss = \$0	1,268,831	32.28%
Loss < \$0.1	1,338,557	34.05%
Loss < \$0.5	1,627,383	41.40%
Loss < \$1	2,003,177	50.96%
Average loss	3,930,884	\$1.69
Regular Driver		
Loss = \$0	522,123	33.66%
Loss < \$ 0.1	549,801	35.44%
Loss < \$0.5	663,089	42.74%
Loss < \$1	808,792	52.14%
Average loss	1,551,314	\$1.68
Relief Driver		
Loss = \$0	746,708	31.38%
Loss < \$0.1	788,756	33.15%
Loss < \$0.5	964,294	40.52%
Loss < \$1	1,194,385	50.19%
Average loss	2,379,570	\$1.71

Note: Loss is defined as the difference between the option value of a driver's actual search decision and the option value of the driver's best search decision. All losses are measured in Singapore dollars.

Table 3: Decision Classification by Strategic Effort and by Risk Preference

Panel A:	Strategic Thinking	
	$\tau = 0.165$	
Level 0 decision	3,366,249	85.64%
Level 1 decision	15,955	0.41%
Level ≥ 1 decision	384,049	9.77%
Level 2 decision	10,745	0.27%
	$\tau = 1.5$	
Level 0 decision	3,332,197	84.77%
Level 1 decision	66,012	1.68%
Level ≥ 1 decision	333,992	8.50%
Level 2 decision	44,797	1.14%
Decisions not classified	153,886	3.91%
Panel B:	Risk Preference	
Minimum mean-adjusted earning variance	586,024	14.91%
Maximum pick-up probability	955,435	24.31%

Note: We classify search decisions by levels of drivers' strategic effort in Panel A. Drivers who make level-0 decision randomly choose among all markets adjacent to his current location. Level ≥ 1 decisions are decisions shared by level-1 and above. Decisions not classified are the choices of non-adjacent markets.
We classify search decisions by two risk-minimizing decision rules in panel B: decisions which coincide with the minimum mean-adjusted earning variance and decisions which coincide with the maximum pick-up probability among the adjacent markets.

Table 4: Earning Loss with Market Knowledge, Strategic Thinking and Risk Preference

Dependent Variable	Earning loss at decision level			
	All Drivers	All Drivers	Regular	Relief
	(1)	(2)	(3)	(4)
Familiarity with optimal market		-4.1309***	-3.8153***	-4.3630***
		[0.1700]	[0.2219]	[0.2477]
Familiarity with current market		-0.6112***	-0.7139***	-0.5529***
		[0.0456]	[0.0678]	[0.0600]
Level 0 decision		-4.4550***	-5.1983***	-4.1051***
		[0.3038]	[0.4762]	[0.3787]
Level $\geq$ 1 decision		-4.0179***	-4.6668***	-3.9237***
		[0.5199]	[0.7151]	[0.6927]
Earning risk minimizing decision		-0.0766	-0.0745	-0.0451
		[0.1929]	[0.3196]	[0.2394]
Pick-up prob. maximizing decision		-0.8599**	-1.1150**	-0.5605
		[0.4061]	[0.5639]	[0.5614]
Short-trip preference		-0.6026***	-0.7104***	-0.5370***
		[0.0747]	[0.1094]	[0.1001]
Current cumulative working time (log)	-0.0022	0.0186***	0.0142***	0.0224***
	[0.0024]	[0.0025]	[0.0036]	[0.0035]
Current cumulative earning (log)	0.0073*	-0.0444***	-0.0269***	-0.0541***
	[0.0043]	[0.0045]	[0.0068]	[0.0060]
Decision before a break	0.0615***	0.0327***	0.0621***	0.0158*
	[0.0063]	[0.0071]	[0.0103]	[0.0094]
Total number of phone bookings	-0.0006***	-0.0008***	-0.0008***	-0.0008***
	[0.0000]	[0.0001]	[0.0001]	[0.0001]
Experience, age and education controls	Yes	Yes	Yes	Yes
Pick-up probabilities	Yes	Yes	Yes	Yes
Day of week and starting hour FE	Yes	Yes	Yes	Yes
Observations	2,604,432	2,604,432	1,039,133	1,565,299
R-squared	0.0449	0.0803	0.0835	0.0787

Note: The estimation sample includes all observations from May to June. Data in April are used to derive the driver-specific characteristics. Familiarity variables are defined as percentage time the driver spent in each district in April. Level-k decision variables are proportions of the driver's decisions in April corresponding to level-k. Similarly, the earning-risk-minimizing-decision variable and the pick-up-probability-maximizing -decision variable are the proportions the driver's decisions in April corresponding to earning-risk-minimizing decision and pick-up-probability-maximizing decision respectively. Pick-up probability and phone bookings are controlled at both current and optimal markets. Clustered standard errors by drivers are shown in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

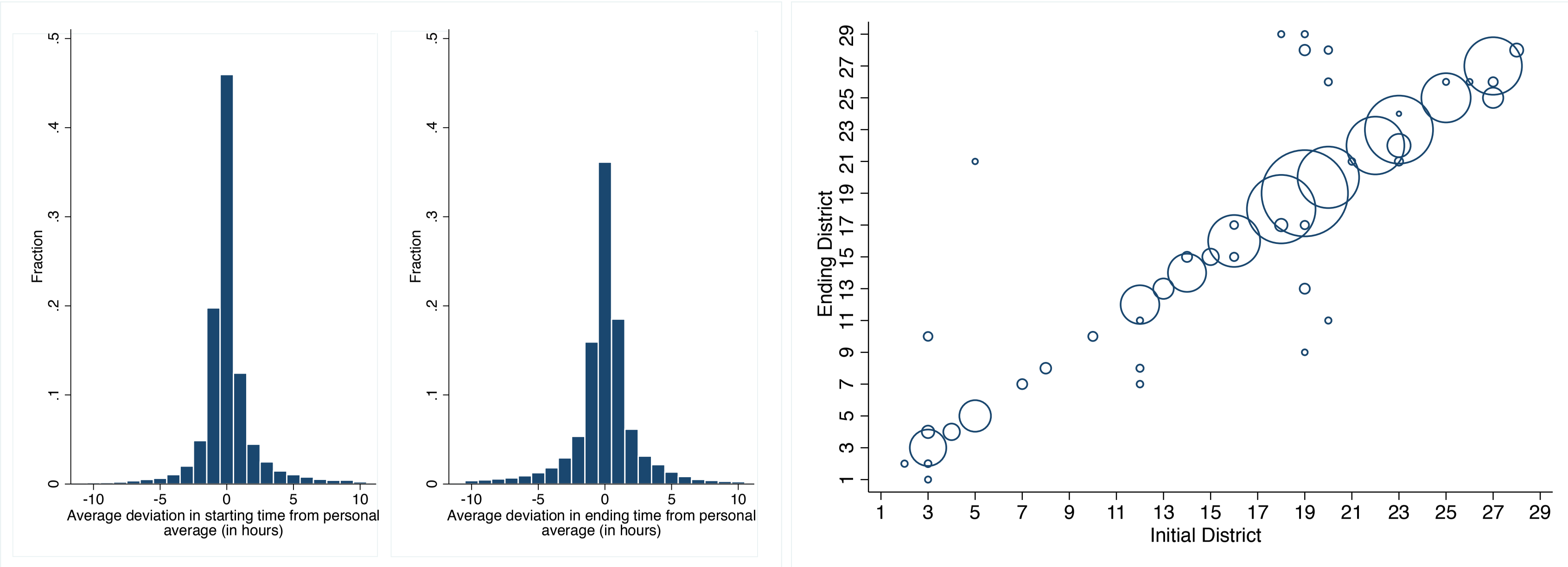


Figure 1: The Distribution of Deviation from Average Starting/Ending Time (left). Starting and Ending Districts of a Shift (right).
Note: The graphs are based on per shift per observation and the bubble sizes are determined by the shift frequency.

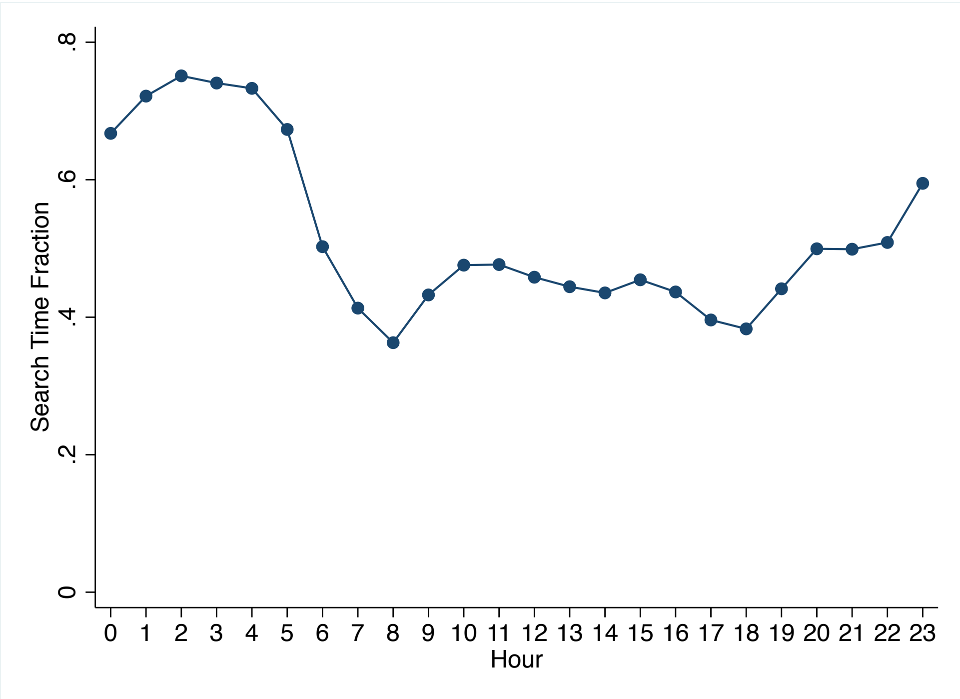


Figure 2: Search Time ("FREE") over Total Work Time ("POB" or "FREE")

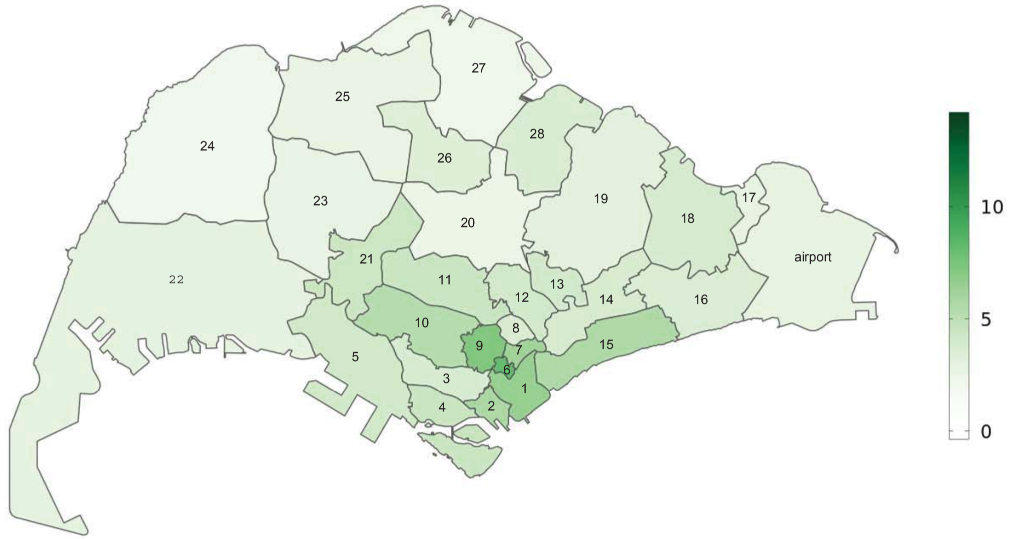


Figure 3: Distribution of Marginal Hourly Wage Rates across All Districts

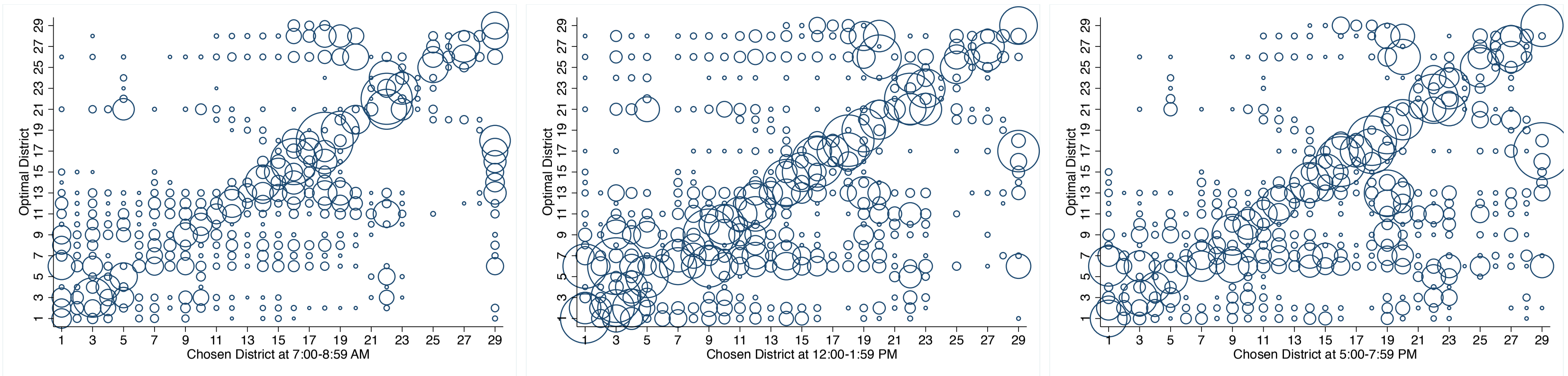


Figure 4: Drivers' Current, Chosen, and Optimal Districts at Three Time Intervals: 7 - 9 a.m., 12 - 2 p.m., 5 - 7 p.m.

References

Buchholz, Nicholas, "Spatial equilibrium, search frictions and efficient regulation in the taxi industry," *Working Paper*, 2019.

Camerer, Colin F, Teck-Hua Ho, and Juin-Kuan Chong, "A cognitive hierarchy model of games," *The Quarterly Journal of Economics*, 2004, *119* (3), 861–898.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler, "Labor supply of New York City cabdrivers: One day at a time," *The Quarterly Journal of Economics*, 1997, *112* (2), 407–441.

Chen, M Keith, Judith A Chevalier, Peter E Rossi, and Emily Oehlsen, "The value of flexible work: Evidence from Uber drivers," Technical Report, National Bureau of Economic Research 2017.

Chiappori, P-A, Steven Levitt, and Timothy Groseclose, "Testing mixed-strategy equilibria when players are heterogeneous: The case of penalty kicks in soccer," *American Economic Review*, 2002, *92* (4), 1138–1151.

Chong, Juin-Kuan, Teck-Hua Ho, and Colin Camerer, "A generalized cognitive hierarchy model of games," *Games and Economic Behavior*, 2016, *99*, 257–274.

Cramer, Judd and Alan B Krueger, "Disruptive change in the taxi business: The case of Uber," *American Economic Review*, 2016, *106* (5), 177–82.

Crawford, Vincent P and Juanjuan Meng, "New york city cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income," *American Economic Review*, 2011, *101* (5), 1912–32.

_ , Miguel A Costa-Gomes, and Nagore Iriberri, "Structural models of nonequilibrium strategic thinking: Theory, evidence, and applications," *Journal of Economic Literature*, 2013, *51* (1), 5–62.

DellaVigna, Stefano and Matthew Gentzkow, "Uniform pricing in us retail chains," *The Quarterly Journal of Economics*, 2019, *134* (4), 2011–2084.

Erev, Ido and Amnon Rapoport, "Coordination,"magic," and reinforcement learning in a market entry game," *Games and Economic Behavior*, 1998, *23* (2), 146–175.

Farber, Henry S, "Reference-dependent preferences and labor supply: The case of New York City taxi drivers," *American Economic Review*, 2008, *98* (3), 1069–82.

Frechette, Guillaume R, Alessandro Lizzeri, and Tobias Salz, "Frictions in a competitive, regulated market: Evidence from taxis," *American Economic Review*, 2019, *109* (8), 2954–92.

Goldfarb, Avi and Botao Yang, "Are all managers created equal?," *Journal of Marketing research*, 2009, *46* (5), 612–622.

— **and Mo Xiao**, "Who thinks about the competition? Managerial ability and strategic entry in US local telephone markets," *American Economic Review*, 2011, *101* (7), 3130–61.

Haggag, Kareem, Brian McManus, and Giovanni Paci, "Learning by driving: Productivity improvements by new york city taxi drivers," *American Economic Journal: Applied Economics*, 2017, *9* (1), 70–95.

Hall, Jonathan V, John J Horton, and Daniel T Knoepfle, "Labor Market Equilibration: Evidence from Uber," Technical Report, Working Paper, 1–42 2017.

Ho, Teck-Hua, Lawrence Jin, and Juin-Kuan Chong, "Earn more by driving less," *Working Paper*, 2020.

Hortaçsu, Ali, Fernando Luco, Steven L Puller, and Dongni Zhu, "Does strategic ability affect efficiency? Evidence from electricity markets," *American Economic Review*, 2019, *109* (12), 4302–42.

Lagos, Ricardo, "An analysis of the market for taxicab rides in New York City," *International Economic Review*, 2003, *44* (2), 423–434.

Levine, Sheen S, Mark Bernard, and Rosemarie Nagel, "Strategic intelligence: The cognitive capability to anticipate competitor behavior," *Strategic Management Journal*, 2017, *38* (12), 2390–2423.

List, John A, "Does market experience eliminate market anomalies?," *The Quarterly Journal of Economics*, 2003, *118* (1), 41–71.

Moore, Don A, John M Oesch, and Charlene Zietsma, "What competition? Myopic self-focus in market-entry decisions," *Organization Science*, 2007, *18* (3), 440–454.

Palacios-Huerta, Ignacio, "Professionals play minimax," *The Review of Economic Studies*, 2003, *70* (2), 395–415.

Rapoport, Amnon, Darryl A Seale, Ido Erev, and James A Sundali, "Equilibrium play in large group market entry games," *Management Science*, 1998, *44* (1), 119–141.

Romer, David, "Do firms maximize? Evidence from professional football," *Journal of Political Economy*, 2006, *114* (2), 340–365.

Simonsohn, Uri, "eBay's crowded evenings: Competition neglect in market entry decisions," *Management science*, 2010, *56* (7), 1060–1073.

Thakral, Neil and Linh T Tô, "Daily labor supply and adaptive reference points," *American Economic Review*, Forthcoming.

A Appendix

Table A1: Average Trip Length and Pick-up Probability

District	Time 6:00-23:59		Time 0:00-5:59		Travel Cost/Friction	
	Mean trip length (min)	Pick-up probability	Mean trip length (min)	Pick-up probability	Minimum S$	Maximum S$
1	15.1	26.3%	15.0	18.3%	0.6	5.6
2	17.2	24.2%	16.4	16.4%	0.6	5.6
3	15.7	29.3%	14.1	21.1%	0.7	7
4	18.4	22.9%	16.8	15.6%	0.5	6.5
5	17.5	26.8%	14.9	11.5%	0.6	6.6
6	15.0	33.0%	14.2	25.5%	0.8	7.4
7	15.4	28.4%	13.1	17.9%	0.7	6.8
8	16.5	23.4%	13.5	11.9%	0.6	5.3
9	15.5	35.2%	14.4	24.7%	0.8	7.8
10	15.6	31.9%	14.2	17.9%	0.8	7.5
11	17.2	34.9%	15.3	23.4%	0.8	6.9
12	16.2	31.0%	13.1	19.2%	0.7	6.5
13	17.0	35.1%	13.9	21.9%	0.8	6.9
14	16.3	32.3%	12.5	15.1%	0.8	6.7
15	15.4	30.2%	13.2	16.5%	0.7	7.3
16	16.8	26.7%	13.0	13.2%	0.6	5.8
17	20.0	27.4%	16.3	16.9%	0.7	7.1
18	15.9	27.5%	12.4	12.8%	0.7	6.3
19	16.5	22.2%	12.0	10.8%	0.5	6.0
20	16.5	22.7%	12.7	8.7%	0.5	6.0
21	19.6	27.4%	16.3	12.5%	0.7	6.1
22	17.1	23.3%	13.1	10.8%	0.6	6.3
23	18.7	20.1%	14.3	8.4%	0.5	4.9
24	18.6	9.6%	12.5	6.8%	0.2	2.9
25	18.7	20.1%	14.5	8.0%	0.5	5.1
26	21.0	31.3%	15.9	18.3%	0.8	7.7
27	18.3	19.1%	13.9	7.3%	0.5	4.3
28	19.3	23.8%	15.2	12.5%	0.6	5.5
29	23.7	9.2%	18.3	7.8%	0.2	2.4

Table A2: Average Marginal Earnings across Districts by Month

Dependent variable	Hourly earnings (dollar)		
	(1) April	(2) May	(3) June
Work time in D1	6.350***	6.552***	6.643***
	[0.180]	[0.176]	[0.172]
Work time in D2	5.302***	6.168***	5.921***
	[0.319]	[0.303]	[0.269]
Work time in D3	3.905***	3.734***	3.752***
	[0.139]	[0.143]	[0.140]
Work time in D4	4.535***	4.685***	4.355***
	[0.168]	[0.177]	[0.173]
Work time in D5	4.114***	4.194***	4.081***
	[0.155]	[0.166]	[0.166]
Work time in D6	7.664***	8.261***	8.770***
	[0.367]	[0.397]	[0.409]
Work time in D7	6.117***	6.311***	6.121***
	[0.203]	[0.221]	[0.220]
Work time in D8	3.691***	3.599***	3.791***
	[0.215]	[0.224]	[0.207]
Work time in D9	7.060***	7.282***	7.358***
	[0.171]	[0.177]	[0.183]
Work time in D10	5.311***	5.428***	5.521***
	[0.161]	[0.173]	[0.170]
Work time in D11	4.308***	4.529***	4.630***
	[0.170]	[0.176]	[0.180]
Work time in D12	4.063***	4.054***	4.099***
	[0.171]	[0.170]	[0.166]
Work time in D13	4.082***	4.349***	3.739***
	[0.241]	[0.271]	[0.238]
Work time in D14	3.811***	3.674***	3.999***
	[0.145]	[0.147]	[0.148]
Work time in D15	5.469***	5.521***	5.793***
	[0.185]	[0.192]	[0.187]
Work time in D16	3.368***	3.774***	3.627***
	[0.129]	[0.137]	[0.133]
Work time in D17	2.665***	2.986***	3.111***
	[0.162]	[0.178]	[0.168]
Work time in D18	3.664***	3.908***	3.864***
	[0.152]	[0.146]	[0.143]
Work time in D19	3.165***	3.168***	3.409***
	[0.130]	[0.133]	[0.132]
Work time in D20	2.657***	2.490***	2.585***
	[0.132]	[0.136]	[0.128]
Work time in D21	4.338***	4.373***	4.448***
	[0.243]	[0.257]	[0.260]
Work time in D22	2.953***	3.056***	3.150***
	[0.120]	[0.117]	[0.122]
Work time in D23	2.700***	2.759***	2.959***
	[0.139]	[0.151]	[0.158]
Work time in D24	1.106**	3.608***	2.129***
	[0.430]	[0.882]	[0.667]
Work time in D25	2.770***	2.774***	2.834***
	[0.154]	[0.163]	[0.162]
Work time in D26	3.081***	3.573***	3.857***
	[0.273]	[0.306]	[0.316]
Work time in D27	2.399***	2.167***	2.508***
	[0.159]	[0.159]	[0.164]
Work time in D28	3.618***	3.689***	3.717***
	[0.353]	[0.345]	[0.344]
Work time in D29	3.065***	3.088***	3.634***
	[0.140]	[0.144]	[0.145]
Observations	378,410	363,791	391,709
R-squared	0.119	0.121	0.121

Table A3: Average Marginal Earnings across Districts by Month

Dependent variable	Hourly earnings (dollar)					
	Regular Driver			Relief Driver		
	(1) April	(2) May	(3) June	(1) April	(2) May	(3) June
Work time in D1	5.847***	5.798***	5.907***	6.902***	7.293***	7.365***
	[0.252]	[0.235]	[0.234]	[0.254]	[0.257]	[0.248]
Work time in D2	5.014***	5.141***	5.112***	5.657***	7.167***	6.718***
	[0.420]	[0.423]	[0.375]	[0.475]	[0.421]	[0.379]
Work time in D3	2.998***	2.820***	2.875***	4.933***	4.728***	4.703***
	[0.170]	[0.180]	[0.177]	[0.221]	[0.223]	[0.213]
Work time in D4	3.779***	3.608***	3.505***	5.353***	5.795***	5.213***
	[0.228]	[0.233]	[0.226]	[0.240]	[0.260]	[0.260]
Work time in D5	3.307***	3.330***	3.301***	5.025***	5.147***	4.937***
	[0.198]	[0.224]	[0.227]	[0.235]	[0.234]	[0.231]
Work time in D6	6.361***	6.649***	8.127***	8.880***	9.819***	9.381***
	[0.521]	[0.588]	[0.530]	[0.499]	[0.492]	[0.602]
Work time in D7	4.955***	5.086***	4.987***	7.300***	7.468***	7.203***
	[0.262]	[0.297]	[0.297]	[0.296]	[0.315]	[0.315]
Work time in D8	3.136***	2.816***	3.091***	4.256***	4.352***	4.496***
	[0.308]	[0.286]	[0.296]	[0.299]	[0.340]	[0.288]
Work time in D9	6.182***	6.186***	6.015***	7.911***	8.319***	8.659***
	[0.230]	[0.244]	[0.243]	[0.249]	[0.247]	[0.262]
Work time in D10	4.590***	4.567***	4.705***	6.051***	6.328***	6.395***
	[0.210]	[0.238]	[0.227]	[0.244]	[0.242]	[0.246]
Work time in D11	3.294***	3.564***	3.562***	5.541***	5.540***	5.841***
	[0.209]	[0.237]	[0.235]	[0.250]	[0.257]	[0.267]
Work time in D12	3.314***	3.086***	2.983***	4.823***	5.016***	5.279***
	[0.223]	[0.213]	[0.211]	[0.259]	[0.265]	[0.247]
Work time in D13	3.184***	3.659***	2.803***	5.031***	5.053***	4.667***
	[0.310]	[0.397]	[0.317]	[0.360]	[0.366]	[0.359]
Work time in D14	2.974***	2.777***	3.475***	4.695***	4.585***	4.544***
	[0.182]	[0.183]	[0.183]	[0.222]	[0.226]	[0.232]
Work time in D15	4.361***	4.519***	4.706***	6.724***	6.567***	6.912***
	[0.236]	[0.252]	[0.244]	[0.272]	[0.280]	[0.277]
Work time in D16	2.631***	2.821***	2.856***	4.187***	4.806***	4.469***
	[0.170]	[0.181]	[0.174]	[0.188]	[0.196]	[0.194]
Work time in D17	1.849***	2.352***	2.411***	3.558***	3.627***	3.896***
	[0.217]	[0.257]	[0.220]	[0.231]	[0.246]	[0.254]
Work time in D18	3.154***	3.329***	3.142***	4.227***	4.521***	4.636***
	[0.192]	[0.194]	[0.185]	[0.238]	[0.216]	[0.215]
Work time in D19	2.481***	2.423***	2.824***	3.905***	3.948***	4.035***
	[0.175]	[0.176]	[0.189]	[0.186]	[0.195]	[0.184]
Work time in D20	1.866***	1.717***	1.885***	3.537***	3.364***	3.355***
	[0.177]	[0.176]	[0.165]	[0.185]	[0.202]	[0.192]
Work time in D21	3.460***	3.796***	3.998***	5.398***	4.994***	4.945***
	[0.308]	[0.368]	[0.348]	[0.376]	[0.346]	[0.392]
Work time in D22	2.385***	2.443***	2.518***	3.558***	3.709***	3.841***
	[0.158]	[0.158]	[0.166]	[0.179]	[0.172]	[0.173]
Work time in D23	2.089***	1.982***	2.380***	3.383***	3.619***	3.596***
	[0.193]	[0.217]	[0.236]	[0.195]	[0.197]	[0.207]
Work time in D24	0.095	1.447	0.749	2.013***	6.293***	3.483***
	[0.572]	[0.936]	[0.838]	[0.608]	[1.207]	[1.013]
Work time in D25	2.300***	2.404***	2.449***	3.307***	3.221***	3.272***
	[0.214]	[0.230]	[0.226]	[0.221]	[0.229]	[0.233]
Work time in D26	2.244***	2.423***	2.794***	3.950***	4.785***	5.015***
	[0.360]	[0.403]	[0.409]	[0.410]	[0.442]	[0.464]
Work time in D27	1.911***	1.615***	1.667***	2.971***	2.762***	3.395***
	[0.225]	[0.215]	[0.221]	[0.224]	[0.230]	[0.235]
Work time in D28	3.270***	3.468***	3.186***	4.024***	4.027***	4.219***
	[0.481]	[0.488]	[0.505]	[0.504]	[0.487]	[0.467]
Work time in D29	2.373***	2.499***	3.004***	3.804***	3.715***	4.272***
	[0.193]	[0.207]	[0.194]	[0.195]	[0.201]	[0.212]
Constant	6.080***	6.124***	6.255***	5.620***	5.622***	5.698***
	[0.098]	[0.093]	[0.092]	[0.113]	[0.112]	[0.118]
Observations	162,886	154,719	169,697	215,524	209,072	222,012
R-squared	0.105	0.104	0.103	0.128	0.132	0.134

Table A4: Earning Loss Explained by Demographics, Fatigue and Market Knowledge

Dependent Variable	Earning loss at decision level		
	All	Regular	Relief
	(1)	(2)	(3)
Familiarity with optimal market	-4.1145***	-3.8186***	-4.3332***
	[0.1679]	[0.2187]	[0.2455]
Familiarity with current market	-0.6465***	-0.7424***	-0.5964***
	[0.0446]	[0.0671]	[0.0598]
Short-trip preference	-0.3973***	-0.5208***	-0.3148***
	[0.0632]	[0.0995]	[0.0810]
Current cumulative working time (log)	0.0194***	0.0158***	0.0226***
	[0.0026]	[0.0038]	[0.0035]
Current earning time (log)	-0.0465***	-0.0300***	-0.0551***
	[0.0047]	[0.0073]	[0.0060]
Decision before a break	0.0270***	0.0517***	0.0128
	[0.0074]	[0.0109]	[0.0099]
Total number of phone bookings	-0.0008***	-0.0008***	-0.0008***
	[0.0001]	[0.0001]	[0.0001]
Pick-up probabilities	Yes	Yes	Yes
Day of week and starting hour FE	Yes	Yes	Yes
Observations	2,604,432	1,039,133	1,565,299
R-squared	0.0781	0.0813	0.0764

Note: The estimation sample includes all observations from May to June. Data in April are used to derive the driver-specific characteristics. Familiarity variables and short-trip preference are defined percentage time the driver spent in each relevant district in April. Pick-up probability and phone bookings are controlled at both current and optimal markets. Clustered standard errors by drivers are shown in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5: Earning Loss Explained by Strategic Thinking and Risk Preference

Dependent Variable	Earning loss at decision level		
	All	Regular	Relief
	(1)	(2)	(3)
Level 0 decision	-4.7443***	-5.8554***	-4.2446***
	[0.2527]	[0.3919]	[0.3009]
Level $\geq$ 1 decision	-3.9820***	-5.2867***	-3.4087***
	[0.4240]	[0.5719]	[0.5306]
Earning risk minimizing decision	-0.2487**	-0.2135	-0.2324*
	[0.1197]	[0.2124]	[0.1405]
Pick up prob. maximizing decision	-0.6431**	-0.7418*	-0.4591
	[0.3110]	[0.4327]	[0.4023]
Short-trip preference	-0.2130***	-0.2905***	-0.1633***
	[0.0444]	[0.0676]	[0.0566]
Current cumulative working time (log)	-0.0025	-0.0041	-0.0001
	[0.0023]	[0.0034]	[0.0031]
Current cumulative earning (log)	0.0085**	0.0229***	0.0008
	[0.0040]	[0.0061]	[0.0053]
Decision before a break	0.0680***	0.1026***	0.0458***
	[0.0059]	[0.0100]	[0.0072]
Total number of phone bookings	-0.0006***	-0.0006***	-0.0006***
	[0.0001]	[0.0001]	[0.0001]
Experience, age and education controls	Yes	Yes	Yes
Pick-up probabilities	Yes	Yes	Yes
Day of week and starting hour FE	Yes	Yes	Yes
Observations	2,604,432	1,039,133	1,565,299
R-squared	0.0476	0.0527	0.0445

Note: The estimation sample includes all observations from May to June. Data in April are used to derive the driver-specific characteristics. Level-k decision variables are proportions of the driver's decisions in April corresponding to level-k. Similarly, the earning-risk-minimizing -decision variable and the pick-up-probability-maximizing-decision variable are the proportions the driver's decisions in April corresponding to earning-risk-minimizing decision and pick-up-probability-maximizing decision respectively. Pick-up probability and phone bookings are controlled at both current and optimal markets. Clustered standard errors by drivers are shown in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

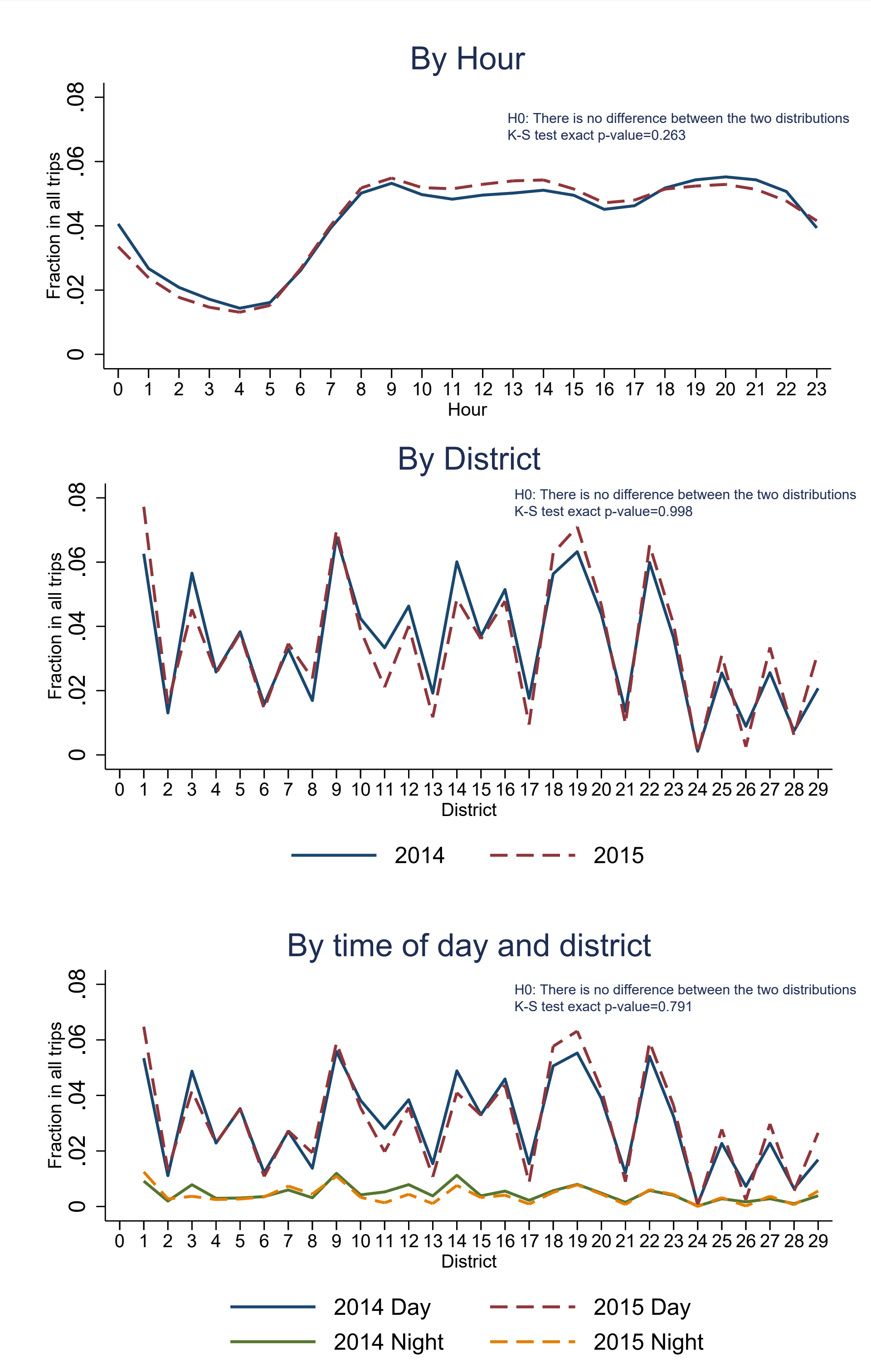
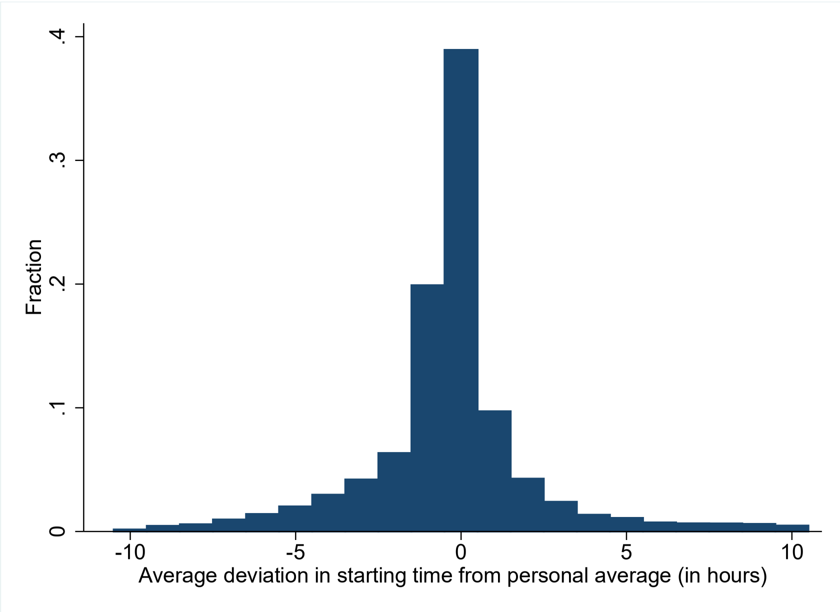


Figure A1: Trip Distributions by Time and Districts for 2014 Sample and 2015 Population



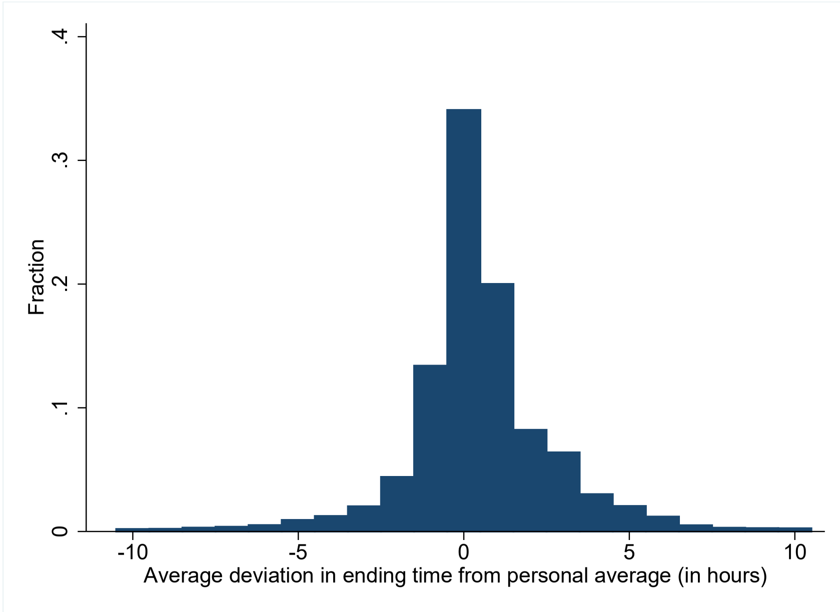


Figure A2: Regular Driver: Deviation from Average Starting/Ending Time (left). Starting and Ending Districts of a Shift (right). Note: The graphs are based on per shift per observation and the bubble sizes are determined by the shift frequency.

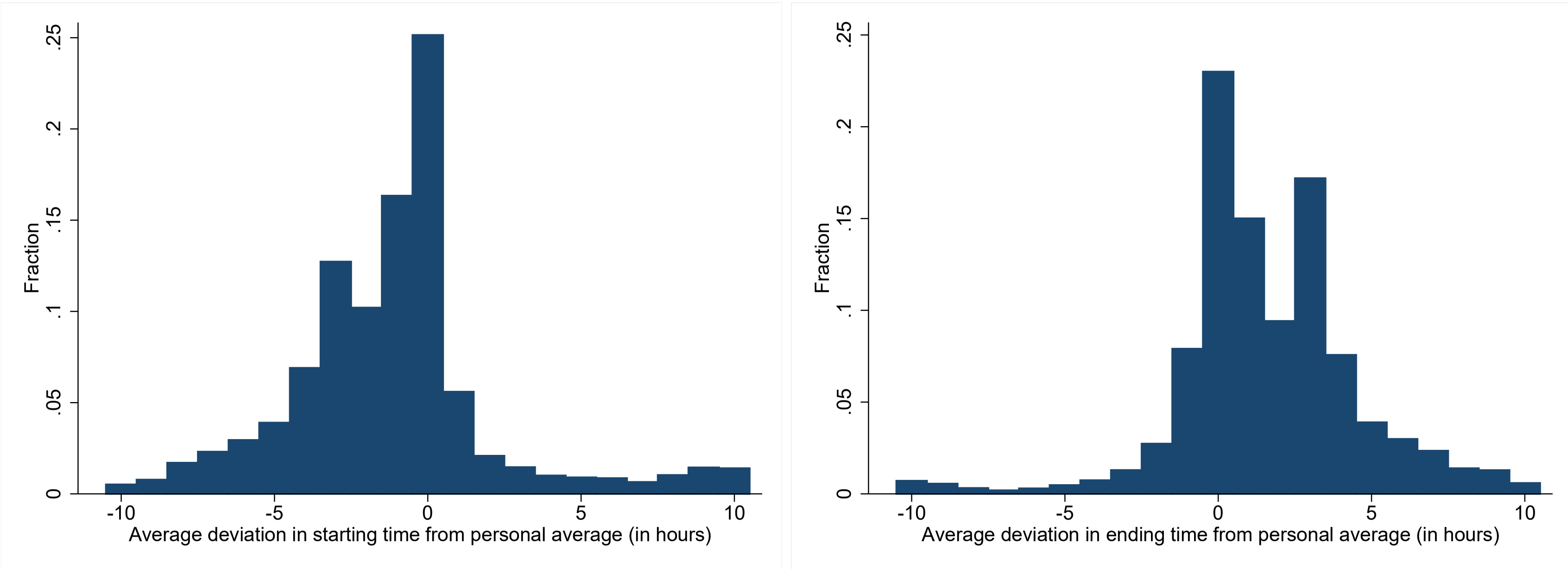


Figure A3: Relief Driver: Deviation from Average Starting/Ending Time (left). Starting and Ending Districts of a Shift (right).
Note: The graphs are based on per shift per observation and the bubble sizes are determined by the shift frequency.

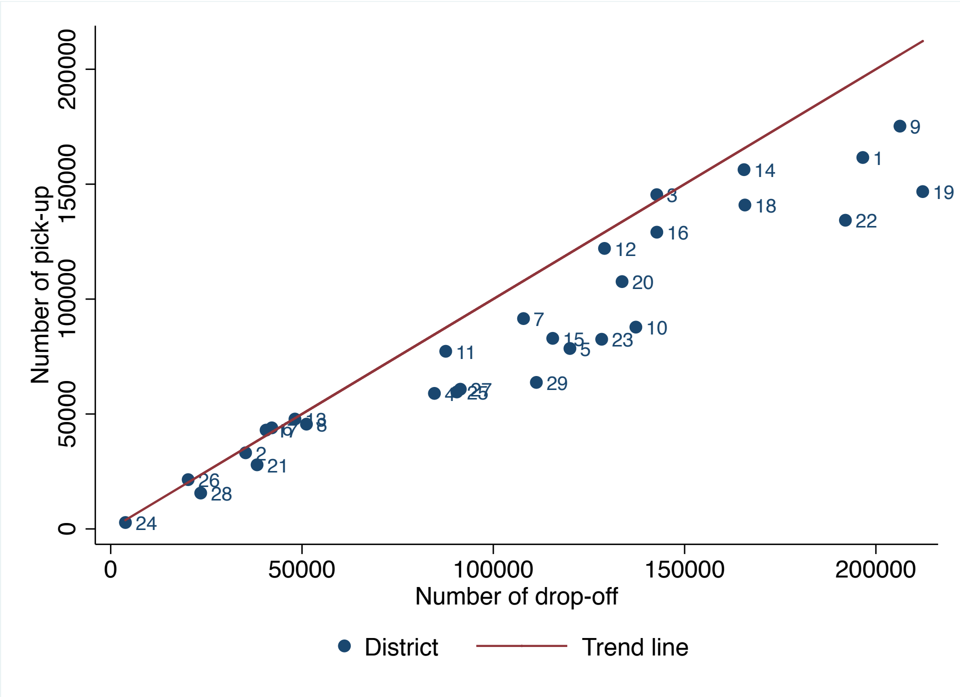


Figure A4: Number of Pick-ups and Drop-offs by District

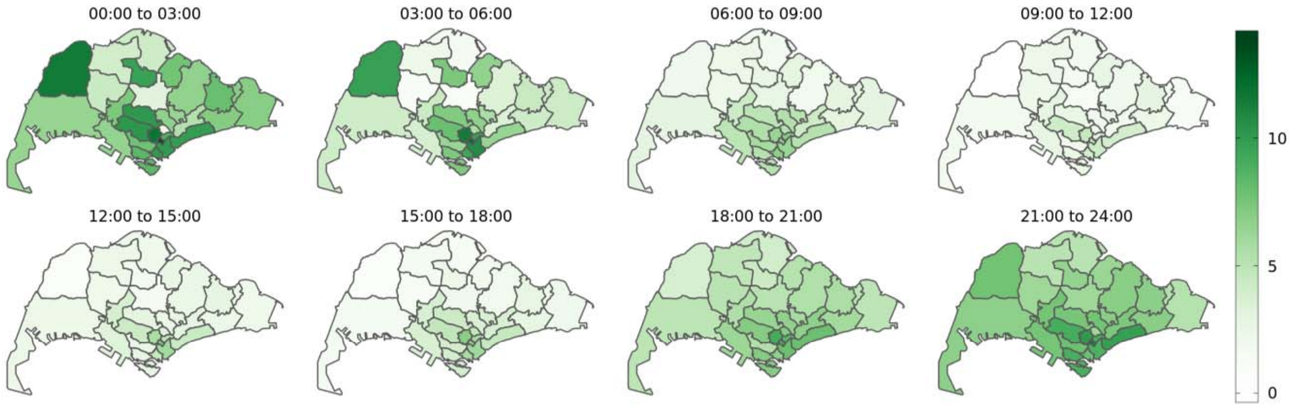


Figure A5: Distribution of Marginal Hourly Wage Rate at Three-Hour Intervals across All Districts