Surge Pricing Moves Uber's Driver-Partners

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Abstract

We study the impact of dynamic pricing (so-called "surge pricing") on relocation decisions by Uber's driver-partners and the corresponding revenue they collected. Using a natural experiment arising from an outage in the system that produces the surge pricing heatmap for a portion of Uber's driver-partners over 10 major cities, and a difference-in-differences approach, we study the short-run effect that visibility of the surge heatmap has on 1) drivers' decisions to relocate to areas with higher or lower prices and 2) drivers' revenue. We demonstrate that the ability to see the surge heatmap has a statistically significant impact on both outcomes. Ability to see the surge heatmap explains 10%-60% of Uber drivers' self-positioning decisions, attracts drivers toward areas with higher surge prices, and increases drivers' revenue on surged trips by up to 70%. This suggests that dynamic pricing helps drivers move to where riders' demand is largest, and that the resulting reduction in spatial search friction and spatial mismatch improves waiting times and welfare for both riders and drivers.

1 Introduction

Pricing in ride-sharing markets has generated a swell of recent interest. Recent literature argues that prices offered to riders in these two-sided markets influence the number wishing to take trips [Cohen et al., 2016, Banerjee et al., 2015, Banerjee et al., 2016], and prices offered to drivers determine their availability to fulfill this demand [Cachon et al., 2017, Castillo et al., 2017, Hall et al., 2017]. Pricing may impact driver availability through (1) changing *the number* of drivers driving [Castillo et al., 2017, Hall et al., 2017, Chen and Sheldon, 2016, Hall and Krueger, 2015] by influencing market entry, how many hours drivers drive, or when during the week they drive; and (2) changing *where* drivers drive, conditioned on their having chosen to drive [Bimpikis et al., 2016]. Focusing on (2), we argue that price influences where drivers drive by influencing drivers' expectations about future price and trip volume in locations to which they might relocate. This influence on expectations may be effected (2a) through the *average* or typical price at a a particular location and time of day/week as observed over longer timescales (weeks or months), and/or (2b) through the signaling effect of the current price on price and trip volume in other nearby locations over a shorter timescale (minutes or hours).

The short-run attraction of the current driver-side price (2b) is of particular importance for understanding the role of *dynamic* pricing in ride-sharing markets. In principle, it should be possible to implement the other ways described in which pricing influences driver availability (1, 2a) through an essentially deterministic driver-pricing approach. Only short-run attraction need be effected via a dynamic pricing approach, like Uber's surge multipliers.

Moreover, anecdotal evidence is ambiguous on whether short-run attraction is significant. We focus on the Uber platform, where dynamic driver-side pricing is actuated through a "surge multiplier" that multiplies the fare that a driver-partner would otherwise receive for a trip. While some drivers on the Uber platform do report responding to the real-time value of the surge multiplier, others advise against "chasing surge" [Campbell, 2017], suggesting that variability in surge prices and the costs of changing one's location makes reacting too strongly to surge prices disadvantageous.

If the short-run attraction of dynamic pricing is insignificant, and driver-side pricing's effect on driver availability operates exclusively at slower timescales of weeks or months, one could conceivably redesign today's ride-sharing platforms to use a deterministic or slowly-varying driver-side pricing approach that could be posted in advance, together with a more dynamic rider-side pricing approach that reacts to unanticipated short-term fluctuations in demand. This alternate deterministic driver-side pricing approach would approximately replicate the average values of today's dynamic approach by location and time of week, providing the influences (1) and (2a) from above, but the schedule of prices by time and location would be the same (or approximately the same) in each week. The ability of such an alternate approach to match the value provided by today's markets is of particular interest because the dynamic nature of Uber's surge prices has been specifically questioned within the popular press [Scheiber, 2017, Goncharova, 2017, McGoogan, 2017].

On the other hand, if the short-run attraction of dynamic pricing is significant, this suggests that dynamic driver-pricing provides value in ride-sharing markets by reducing spatial search friction. Reducing spatial search friction reduces mismatch between the number of riders wishing to take trips and the number of drivers willing to drive, which reduces waiting times, increases the number of trips taken, and improves welfare for both sides of the market. The importance of keeping spatial search friction low is argued by [Buchholz, 2015], which studies these frictions in taxi markets. That paper argues that spatial search frictions create significant losses in consumer welfare in taxi markets, and that the growth in ride-sharing is "suggestive of the enormous benefits associated with reduced search costs compared with traditional taxi markets."

In this paper, we study empirically whether short-run variation in dynamic prices attracts drivers. We use a natural experiment in which Uber's surge prices ceased to be visible for drivers using phones on the iOS operating system in 10 of its largest markets. Using a difference-in-differences approach [Ashenfelter and Card, 1984, Card, 1990], and controlling for confounding factors arising from differences in the populations that use each operating system, we provide evidence that dynamic surge prices do have a significant effect on drivers' self-positioning decisions, causing drivers to drive toward nearby areas with higher surge values. We also show that having access to real-time information from the surge heatmap increased unaffected drivers' revenue, controlling for systematic differences between drivers using iOS and Android phones.

This suggests that dynamic pricing is indeed useful as a real-time signaling tool for reducing spatial search frictions in the ride-sharing market, better aligning drivers' locations with riders' desire to take trips. This further suggests that a reduction in search frictions realized by the dynamic nature of surge pricing reduces waiting times and improves welfare for riders and drivers. This value is in addition to the slower-timescale alignment between riders' demand and drivers (1, 2a above) realized by allowing the average surge multiple to vary over time and space. Moreover, similar mismatch occurs in other two-sided markets where labor is constrained in space, time, skill-set, specialty, or regulatory licenses. Our results suggest that dynamic pricing has the potential to reduce spatial search frictions in these other settings.

The use of a natural experiment is critical for answering the question of whether information provided by the surge heatmap causes drivers to relocate over short timescales. This is because endogeneity is particularly problematic for understanding causality between surge multipliers' and drivers' repositioning decisions. As noted above (2a), drivers learn the areas of their city in which demand tends to outstrip supply, and they tend to drive toward those areas to benefit from shorter wait times between trips and higher surge multiplies. If drivers make these repositioning decisions exclusively based on their knowledge of average surge multiples, and not based on the real-time information present in the current surge heatmap, then we would nevertheless expect to see a correlation between surge multipliers and drivers' repositioning decisions. The natural experiment allows us to disentangle these effects. Using a difference-in-differences approach within a multinomial logit discrete choice model, we can compare the relocation decisions and driver revenue on the outage weekend among iOS drivers with an estimate for what these decisions and driver revenue would have been without the outage based on data from other weekends on all drivers, and data from the outage weekend from unaffected Android drivers.

In addition to the work cited above on ridesharing, our work is also related to the larger literature on spatial mobility in labor markets [Morrison, 2005], and in particular to empirical analyses of the spatial elasticity of labor supply [Manning, 2003, Chapter 9], [Madden, 1977]. While related, this literature has typically focused on spatial mobility over longer time and spatial scales. More generally, our work can be viewed within the larger literature on informational and physical frictions in labor markets [Morrison, 2005]. This literature often focuses on search [Rogerson et al., 2005], and within this context, the surge heatmap can be seen as an aid that reduces the cost of search for drivers in the ridesharing market.

The rest of the paper is organized as follows. Section 2 starts with a description of Uber's pricing system, the data we use in our estimation, and the natural experiment. Section 3 then describes our methodology, including a multinomial-logit driver behavior model and our difference-in-differences estimation approach. Section 4 discusses assumptions made in our methodology. Section 5 provides results and discusses implications for the effects of dynamic pricing on both driver movement and driver revenue. Finally, Section 6 summarizes with conclusions.

2 Background, Data Overview, and Description of the Natural Experiment

We now provide background on Uber's surge pricing system, an overview of the data used to perform our analysis, and a description of the natural experiment.

2.1 Background on Uber's Surge Pricing System

Uber operates a two-sided market in which individuals wishing to take a trip ("riders") are matched with other individuals willing to drive them for a fee ("drivers"). The rider requests a trip via a smartphone application, the "rider app", and the driver accepts or rejects dispatch requests via another smartphone application, the "driver app". We focus on the UberX service in which a single rider or party of riders occupies a car, and do not discuss other Uber products.

At the time when the natural experiment we analyze occurred, both the price paid by the rider and the fee earned by the driver for participating in the UberX service were both set via a "surge multiplier" and the "unsurged fare". The unsurged fare was computed from the time and distance traveled by the driver with the rider in the vehicle via a fixed city-specific linear functon, while the surge multiplier was computed dynamically as described below. The rider price was then obtained by multiplying the unsurged fare by the surge multiplier. The driver's revenue resulting from the trip was then calculated by removing a fixed commission from the total amount paid by the rider.

Cities are partitioned into non-overlapping uniform hexagons, each with an edge length of 0.2 miles (0.32km). Each hexagon is assigned its own surge multiplier, which is recalculated regularly and applied to all trips starting in that hexagon over that two minute period.

Uber sets surge multipliers dynamically and algorithmically. This algorithm sets surge multiplier based on the number of riders in the process of using the rider app to make trip requests in a geographically localized area, the number of driver partners in or near that area who have made themselves available to conduct trips via the driver app, as well as some additional factors.

The surge pricing algorithm is designed to protect the health of the dispatch marketplace by balancing supply and demand in real time: when the number of trip requests seems likely to exceed the ability of the market to efficiently fulfill them, it increases the surge multiplier to ration demand, and to attract drivers to the undersupplied area.

It is reasonable to expect that drivers would prefer to be in hexagons with high surge multipliers, both because a higher surge multiplier results in a larger payment to the driver holding fixed a trip's time and distance, and because a higher surge multiplier typically indicates that the ratio of riders to drivers is high and thus a driver's waiting time for a trip will be short. Uber also prefers drivers to move to areas with higher surge multipliers, because their presence in high-demand areas allows more riders to take trips with lower waiting times.

To support this movement toward surging areas, the driver app shows a visualization called the "surge heatmap" (see Figure 1) that displays the current surge multiplier in each hexagon. Drivers can see this surge heatmap when they have indicated in the driver app they will consider dispatch requests and they are not currently servicing a request. We call such drivers in the "open" state. Drivers who are unwilling to consider dispatch requests (either because they have indicated so in the app, or the app is turned off) are considered to be in the "offline" state. Once a rider is matched with an open driver, the driver is given directions on where to meet the

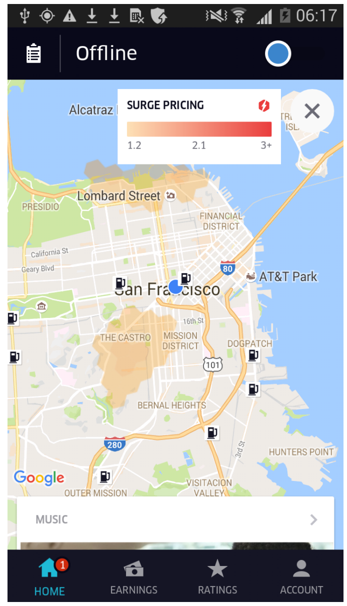


Figure 1: Screenshot of the surge heatmap in the Uber driver app. The surge heatmap shows the current value of the surge multiplier in each hexagon to driver partners.

rider and the surge heatmap is no longer visible. We call drivers on their way to pick up a rider "en route," and drivers who are driving with a rider in the car "on-trip."

In the following sections we describe mathematical methodology used to model driver behavior in response to this surge heatmap and other information they may have, in preparation for describing and analyzing a natural experiment pertinent to the question of whether drivers' movement decisions are influenced by this surge heatmap.

2.2 Data Overview

We use data from four data sources: 1) surge heatmap data; 2) driver location data; 3) operating system information; 4) driver metadata. We now describe these sources in detail.

Surge heatmap data: Surge multipliers are recorded for each hexagon and in each minute. During periods of normal operation, these surge multipliers are made available to all drivers using the Uber driver app, including those that are offline.

Driver location data: GPS data from each driver's phone is recorded while he or she is open, en-route, on trip, or offline and observing the surge heatmap. Recording facilitates matching drivers with nearby riders and providing accurate estimated times of arrival to riders while the driver is en-route and on trip. From this data, we extract the hexagon each open driver occupies in each minute during the time period analyzed.

Operating system information: Each driver account may have only one phone online at any point in time. The operating system (OS) run by this phone is made available to Uber's servers as part of the process of communicating with that phone. We record the identify of this OS (iOS or Android) along with the driver's location data. A driver may complete a session on his or her driver account with one phone and then start a new session with another phone that has a different OS. In this case, the OS associated with that driver's location data before the change would reflect the first phone's OS, and the the data recorded after would reflect the second phone's OS.

Driver metadata: When drivers sign up on the Uber platform, information about the driver is recorded as part of the background check process. We extract from this data the driver's age and the date on which the driver signed up. We convert the signup date to the driver's tenure, i.e., the length of time since that driver signed up at the time of the period of analysis.

Combined dataset: We combine these four datasets to create a dataset ready for analysis. An example is given in Table 2. Each row describes one driver-minute and includes a unique identifier for the driver, the time, the driver's current hexagon, the hexagon that the driver occupied in the next minute, surge multipliers for the driver's current hexagon and all adjacent hexagons, the OS on the phone currently being used by the driver, and the driver's age and tenure. Table 1 provides summary statistics from this dataset.

2.3 Description of the Natural Experiment

During the weekend of November 4th to 6th in 2016, cities served by one of Uber's data centers suffered from a technical outage in the surge pricing system. These cities included New York City, Boston, Chicago, Washington DC, and many other cities in the United States and around the world. In the affected cities, drivers using the driver app on an iOS phone (so-called "iOS drivers") received a blank heatmap without surge information, consistent with what they would see if the surge multiple were identically 1 across the city. Drivers using the driver app on an Android phone (so-called "Android drivers") could see the surge heatmap as usual. The outage only affected iOS drivers' ability to *see* the surge heatmap, but did not change the way in which they earned.

The dispatch screen shown to drivers when they are offered a trip indicates the surge multiple, and this was working normally. Thus, while some drivers at some times were likely unaware that there was an outage and simply thought no areas were surging, many drivers would have quickly become aware that the surge heatmap was not working, especially those positioned in parts of the city that were surging.

The natural experiment enables us to study the impact of the lack of visibility of the surge heatmap on drivers by, roughly speaking, comparing the difference between iOS and Android drivers on the outage week and another non-outage week, while controlling for systematic differences between these two groups. If lack of visibility has an impact, then this difference between iOS and Android drivers should change significantly during the outage week. For the weekend unaffected by the outage, we gathered data from the weekend of 10/22 to 10/24. This skips the immediately previous Halloween weekend, since Halloween is one of Uber's busiest days and causes unusual activity.

3 Methodology

We analyze driver movements using a multinomial logit (MNL) model over drivers' direction of motion. This MNL model uses utility determined by a factor model over the change in surge multiplier in each direction of movement, the visibility of the surge heatmap, the driver's operating system, a time indicator controlling for changes in driver movement between the outage and non-outage weeks, and driver covariates intended to control for differences in behavior between iOS and Android drivers. Under assumptions of zero coefficients for the two-way interaction (operating system) $\times$ (time) and for the three-way interaction (operating system) $\times$ (time) $\times$ (surge multiplier change), and under the parametric and independence assumptions implicit in this model, this analysis is able to identify the impact of making the surge heatmap visible to drivers. Limitations of this modeling approach are discussed in more detail in section 4 and results are presented in section 5.

We now describe this methodology in detail, first summarizing the MNL model (section 3.1) and factor utility model (section 3.2), and finally describing how the MNL and factor utility model were applied to analyze the natural experiment within a DiD framework (section 3.3). We then present limitations of this approach and study its assumptions in section 4 and present results in section 5.

3.1 A Model of Driver Behavior

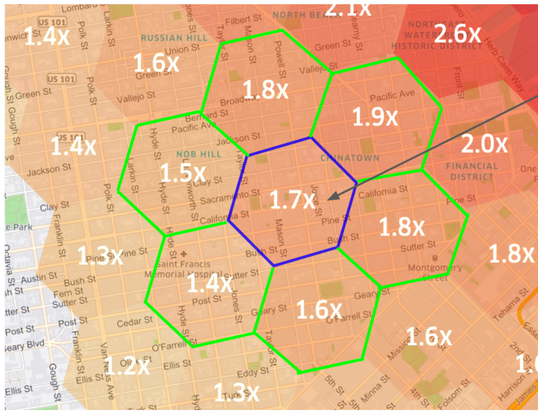
Consider a driver d in the open state at minute t in hexagon i, deciding whether to stay or move. We are interested in this driver's desired direction of motion. To study this, we record his state (open, en-route, on-trip, or offline) at minute $t+1$, and if he is open, en-route or on-trip we record his location. For drivers that are open at minute $t+1$, we determine whether each driver remains in the same hexagon i (indicating this lack of motion by $j = 0$), has moved to one of the 6 immediately adjacent hexagons (indicating these directions of motion by $j \in \{1, 2, \ldots, 6\}$), or has moved to some other hexagon. We model the selection j as a choice made by a driver. This choice is illustrated below in Figure 2.

Drivers that are not open at minute $t + 1$ or that move to a hexagon outside i and its 6 immediate neighbors are treated making choices that are unobserved. The most frequent cause for not being open at time $t + 1$ is a driver's being dispatched, placing them in en-route state. Drivers can cross two hexagons in 1 minute if they are on a highway or another arterial road permitting high-speed travel. The 7 values for j we consider include over 90% of driver movements among drivers that remained open.

We model drivers' choices using a multinomial logit (MNL) discrete choice model [Anderson et al., 1992]. Specifically, we model an open driver's utility of moving in direction j from hexagon i at minute t as

$$u(t, i, j, d) + \xi_{t,i,j,d}.$$

Here, $\xi_{t,i,j,d}$ is an independent Gumbel distributed random variable. $u(t, i, j, d)$ represents the driver's perceived utility of making movement direction j when in hexagon i at time t for a driver with a set of driver features d.



7 options with Prices

	Immediate	Smoothed
0	1.7x (+0.0x)	1.69x (+0.0x)
1	1.9x (+0.2x)	2.02x (+0.33x)
2	1.8x (+0.1x)	1.83x (+0.14x)
3	1.6x (-0.1x)	1.57x (-0.12x)
4	1.4x (-0.3x)	1.33x (-0.36x)
5	1.5x (-0.2x)	1.37x (-0.32x)
6	1.8x (+0.1x)	1.84x (+0.15x)

Figure 2: The figure illustrates a driver at an origin hexagon i (outlined in blue) choosing which hexagon to move to next (adjacent hexagons are outlined in green). We model this choice as being correlated with the change in smoothed surge multiplier (shown at right) between the origin hexagon and the 3 hexagons in the chosen direction of motion.

We will discuss the form of $u(t,i,j,d)$ in detail below.

While this model, conditioned on having an observation (which includes, for example, the condition that the driver is not dispatched), and given a particular utility function, the probability of observing choice j is,

$$P(j|t,i,d) = \frac{\exp(u(t,i,j,d))}{\sum_{j'=0}^{6}\exp(u(t,i,j',d))}.$$

A number of factors may contribute to a driver's choice of j. We are interested most importantly in the causal effect of the surge multiplier, but also the confounding effect that motion may be correlated with the surge multiplier because drivers tend to move toward high-demand areas and high-demand areas tend to surge. To allow our model to capture the dependence of motion on such factors, we include in our utility $u(t,i,j,d)$ the difference in smoothed surge multiplier $\Delta p(t,i,j)$ between the origin hexagon i and for the hexagon in direction j. We will address possible confounding through the natural experiment discussed below.

More precisely, the term $\Delta p(t,i,j)$ is computed by first computing a "smoothed" surge multiplier for each hexagon, obtained by averaging the surge multipliers in the hexagons in three concentric rings. This provides a smoothed surge price for the origin $p(t,i)$ and for the hexagons in the 6 directions $p(t,j)$. Then $\Delta p(t,i,j) = p(t,j) - p(t,i)$ is the difference in these prices. The values of the smoothed surge multipliers and corresponding $\Delta p(t,i,j)$ are presented in the column "Smoothed" in the table in Figure 2. The values in the "Immediate" column are based on the non-smoothed surge multipliers from only a single hexagon. The motivation of using smoothed multipliers is to capture the attraction of surged hexagons that are further away than one ring. When we did not smooth multipliers, we saw similar results on all metrics.

Another factor that may contribute to a driver's choice of j is whether the heatmap was visible when the driver was making his or her decision. This will be encoded through a factor invisible(d,t), which takes a value of 0 for drivers d and times t for which the surge heatmap was visible to open drivers (as is typical), and takes a value of 1 when the heatmap is hidden, as it was in the outage in our natural experiment.

While we discuss in more detail the specific functional form assumed for $u(t, i, j, d)$ in the next section, and discuss assumptions following from that functional form there, we note and briefly discuss assumptions we have made thus far:

A1. $\xi_{t,i,j,d}$ are independent across t, i, j, d. This assumes implicitly and in particular that driver d's decisions are not directly influenced by other drivers in the immediate area. It does, however, allow a driver's decisions to be influenced indirectly by other nearby drivers, through the impact their presence has on surge multipliers and waiting times.

A2. The dependence of $u(t, i, j, d)$ on hexagon i and direction j is only through the price difference $\Delta p(t, i, j)$.

A3. Drivers' movement decisions are not influenced by surge multipliers further than the 4th ring of hexagons from their current hexagon. This is a distance of approximately 1.5 miles.

A4. Observations of drivers movements are censored independently of their unobserved movement decisions.

A5. We assume that the probability distribution describing driver's choices' has the functional form of an MNL model.

We now discuss the functional form of $u(t, i, j, d)$ in detail.

3.2 The Utility Function

Without loss of generality, we normalize the utility of staying in the same hexagon, $u(t, i, 0, d)$, to be 0. The utility of moving in direction j, $u(t, i, j, d)$, then is the change in the driver's utility relative to staying. To model the value of $u(t, i, j, d)$ for $j > 0$, we use a factor model containing the following features:

- the difference in surge multiplier $\Delta p(t, i, j)$ discussed above
- a collection of driver metrics that depend on d: the operating system, the driver's age, and the driver's tenure on the Uber platform. We discuss and motivate these choices below. We indicate these here in a generic way with a vector $x(d)$ with components $x_k(d)$, where k starts at 0.
- the binary indicator invisible(d, t) that is 1 if the heatmap is hidden to drivers and 0 otherwise
- a binary time indicator $T(t)$. Within the analysis of the natural experiment, we will apply our factor model to data collected over two weeks. This indicator will take the value 1 for the week when the outage occurred, and 0 in the previous week.

This model has the following specific form:

$$
\begin{aligned}
u(t,i,j,d) &= \beta_0 + \beta_1 \cdot \Delta p(t,i,j) \\
&\quad + T(t) \cdot [\beta_2 + \beta_3 \cdot \Delta p(t,i,j)] \\
&\quad + \text{invisible}(d,t)[\beta_4 + \beta_5 \cdot \Delta p(t,i,j)] \\
&\quad + \sum_k x_k(d) \cdot [\beta_{6+3k} \cdot + \beta_{7+3k} \cdot \Delta p(t,i,j) + \beta_{8+3k} \cdot T(t) + \beta_{9+3k} \cdot \Delta p(t,i,j) \cdot T(t)]
\end{aligned} \tag{1}
$$

The first row of coefficients includes a constant term β_0, which one can interpret as the value of moving out of the current hexagon if all other factors are 0 (recall that this utility is the value for all $j > 0$, and the utility at $j = 0$ is fixed to 0). It also includes a term β_1 that represents the desirability of moving toward increasing surge multiplier. The second and third rows contains similar terms, but now interacted with the time indicator $T(t)$ in the second row and the surge visibility invisible(d,t) in the third. The fourth row also contains similar terms interacted with each driver feature, and also the interaction of this driver feature with the time indicator and the price difference.

Taken collectively, the sum $\beta_1 + \beta_3 \cdot T(t) + \beta_5 \cdot \text{invisible}(d,t) + \sum_k (\beta_{7+3k} + \beta_{9+3k} \cdot T(t)) \cdot x_k(d)$ represents the dependence of the utility to the surge multiplier gradient, including both dependence due to causal factors (drivers being attracted to areas with higher surge multiplier) and due to non-causal confounding factors (e.g., drivers wishing to move toward areas that have low wait times, that happen to also have higher surge gradients). The coefficient of β_5 determines how this sensitivity changes when the surge heatmap is hidden, and it is on this coefficient that we will focus when using the natural experiment to understand the causal relationship between the surge heatmap and driver movement.

We take note of the model form (1) as an assumption.

A6. We assume that drivers' utility is modeled by the functional form (1).

3.3 Difference-in-Differences Estimation (DID)

To apply the previously discussed model within our natural experiment, we explicitly write our list of driver metrics as $x(d) = (\text{iOS}(d), \text{age}(d), \text{tenure}(d))$. Here, iOS$(d)$ is a binary variable that is 1 if the driver uses an iOS phone; age(d) is a continuous variable storing the driver's age; and tenure(d) is a continuous variable storing the number of years that have passed since the driver signed up to drive with Uber. The choice of iOS(d) allows us to compare drivers that experienced the outage from those that did not, while the two covariates are present to control for systematic differences between iOS and Android drivers, as discussed below.

We then note that the surge heatmap is only hidden during the outage week for iOS drivers. Thus, invisible$(d,t) =$ iOS$(d) \times T(t)$.

We finally make the following additional assumption, in light with the parallel trend assumption ([Card, 1990]) typically made in applications of DID methodology.

A7. The coefficients on the interaction terms $\mathrm{iOS}(d) \cdot T(t)$ and $\mathrm{iOS}(d) \cdot T(t) \cdot \Delta p(t, i, j)$ are 0.

Assumption A7 assumes that the difference between iOS and Android drivers stays the same week over week (except for the outage), and as we change the surge multiplier gradient $\Delta p(t, i, j)$. To help ensure that A7 is met, we include $\mathrm{age}(d)$ and $\mathrm{tenure}(d)$ and their interactions with $T(t)$, $\Delta p(t)$ and $T(t) \cdot \Delta p(t)$ in our regression. This is discussed in more detail in the next section.

Applying these three modeling choices to the utility model (1), we obtain:

$$\begin{aligned} u(t, i, j, d) = \beta_0 &+ \beta_1 \cdot \Delta p(t, i, j) \\ &+ T(t) \cdot [\beta_2 + \beta_3 \cdot \Delta p(t, i, j)] \\ &+ \mathrm{invisible}(d, t) \cdot [\beta_4 + \beta_5 \cdot \Delta p(t, i, j)] \\ &+ \mathrm{tenure}(d) \cdot [\beta_6 + \beta_7 \cdot \Delta p(t, i, j) + \beta_8 \cdot T(t) + \beta_9 \cdot \Delta p(t, i, j) \cdot T(t)] \\ &+ \mathrm{age}(d)[\beta_{10} + \beta_{11} \cdot \Delta p(t, i, j) + \beta_{12} \cdot T(t) + \beta_{13} \cdot \Delta p(t, i, j) \cdot T(t)] \\ &+ \mathrm{iOS}(d) \cdot [\beta_{14} + \beta_{15} \cdot \Delta p(t, i, j)] \end{aligned}$$

To estimate the model parameters, we use maximum likelihood estimation with the likelihood implied by this factor model for the utility and the MNL model over driver decisions j. To create confidence intervals and perform hypothesis tests, we use a bootstrapping approach [Efron, 1992].

Within this model and estimation method, the sensitivity to the surge gradient is given by

$$\begin{aligned} &\beta_1 + \beta_3 \cdot T(t) + \beta_5 \cdot \mathrm{invisible}(d, t) + \beta_7 \cdot \mathrm{tenure}(d) + \beta_9 \cdot \mathrm{tenure}(d) \cdot T(t) + \\ &\beta_{11} \cdot \mathrm{age}(d) + \beta_{13} \cdot \mathrm{age}(d) \cdot T(t) + \beta_{15} \cdot \mathrm{iOS}(d). \end{aligned} \tag{2}$$

With this in mind, we wish to test the following hypotheses about this sensitivity in our analysis:

- that equation (2) is positive (indicating that drivers tend to move toward surge) for typical values of $T(t)$, $\mathrm{tenure}(d)$, $\mathrm{age}(d)$, and $\mathrm{iOS}(d)$ when $\mathrm{invisible}(d, t) = 0$
- β_5 is negative, showing that sensitivity of movement to surge is reduced when the heatmap is not visible
- that equation (2) remains non-negative when $\mathrm{invisible}(d, t) = 1$, showing that lack of visibility of the surge heatmap does not cause drivers to move *away* from surge

Additionally, the coefficient associated with staying in the same place when $\Delta p = 0$ is given by

$$\begin{aligned} &\beta_0 + \beta_2 \cdot T(t) + \beta_4 \cdot \mathrm{invisible}(d, t) + \beta_6 \cdot \mathrm{tenure}(d) + \beta_8 \cdot \mathrm{tenure}(d) \cdot T(t) + \\ &\beta_{10} \cdot \mathrm{age}(d) + \beta_{12} \cdot \mathrm{age}(d) \cdot T(t) + \beta_{14} \cdot \mathrm{iOS}(d) \end{aligned} \tag{3}$$

We wish to test the hypotheses that:

- this coefficient is negative for typical values of $T(t)$, $\mathrm{tenure}(d)$, $\mathrm{age}(d)$, and $\mathrm{iOS}(d)$ when $\mathrm{invisible}(d, t) = 0$.
- this coefficient remains negative when $\mathrm{invisible}(d, t) = 1$.

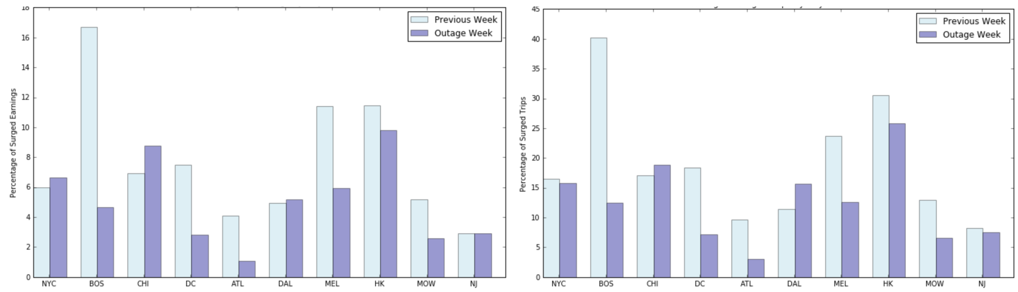


Figure 3: Surge Multipliers Over Time: The left-hand plot shows the percentage of drivers' revenue due to surge. This is shown by weekend (light blue indicates the non-outage weekend, and purple the outage weekend) and city. The right-hand plot shows the percentage of trips surged.

4 Analysis of Model Assumptions

Our approach relies on the assumption (A7) that $\mathrm{iOS}(d) \cdot T(t)$ and $\mathrm{iOS}(d) \cdot T(t) \cdot \Delta p(t, i, j)$ have zero coefficients. To study this assumption, we study the difference between the two weekends in our analysis, and the difference between iOS and Android drivers. We find differences both across weekends and across groups, which are mitigated by controlling for time, operating system, driver age, and driver tenure in our analysis.

4.1 Differences Across Time

Market conditions are determined by the imbalance between demand and supply. On the demand side, large events, weather and traffic conditions influence passengers' need for a ride; on the supply side, incentive campaigns and other opportunity costs affect drivers' driving hours. There is no guarantee that market conditions over any two weekends are similar. Indeed, demand and supply patterns behave differently over the two weekends studied, and the surge pricing algorithms adjusts for the change correspondingly, as shown by the statistics in Figure 3.

In general, the previous weekend was more supply-constrained and consequently surged more. For example, 41% of trips in Boston had a surge multiplier strictly larger than 1 in the previous weekend while only 12% of trips in the outage weekend did. Similarly, surge impacted drivers' income to a different extent over the two weekends. Surge income constituted 17% of all drivers' income during the past week, but only 5% during the outage weekend.

4.2 Differences between the iOS and Android Drivers

Drivers' choice of the phone's operating system (OS) might reflect differences in demographics, which are correlated with their driving habits. To test this, we collected data on drivers' age and tenure (years since singing up for Uber) along with their phones' operating systems. Data exhibited extreme diversity: drivers' age ranged from 18 to 82, and tenure varied from just a few days to over six years.

Figure 4 shows that iOS drivers are on average younger than Android drivers in all cities. However, the ordering of their tenure differs across cities. Specifically, an average iOS drivers has a longer tenure in Chicago

(CHI), Boston (BOS), Washington D.C.(DC), Hong Kong (HK), Moscow (MOW) and New Jersey (NJ), while an average android Android driver has a longer tenure in New York (NYC), Atlanta (ATL), and Dallas (DAL).

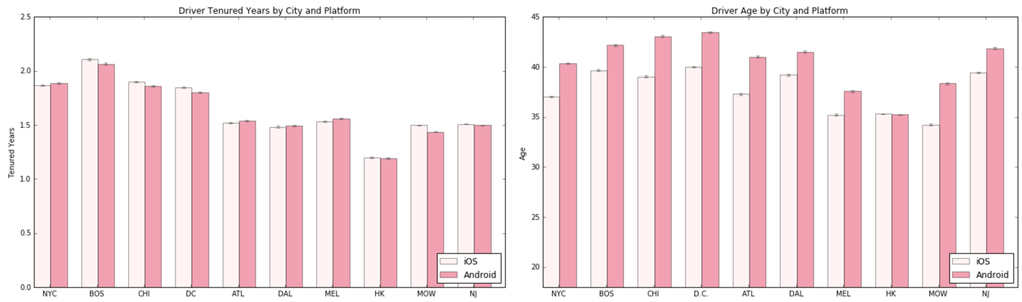


Figure 4: Differences by Operating System: The figures show the tenure (left) and age (right) for iOS and Android Drivers, by city. Confidence intervals for the mean value are shown using the standard deviation of the sample mean.

To address these differences, we include tenure and age as covariates in our factor model, their interactions with $T(t)$ and $\Delta p(t,i,j)$, as well as the covariate $\text{iOS}(d)$.

To further verify Assumption A7, we include in the appendix the results of a DiD analysis with two regular weekends, which concludes that the coefficient on $\text{iOS}(d) \cdot T(t) \cdot \Delta p(t,i,j)$ is 0.

4.3 Composition of Drivers

We hypothesize that the primary mechanism by which invisibility of the surge heatmap affects driver mevoment is through changing drivers' decisions about where to relocate. However, an alternate mechanism may also be at work: invisibility of the surge heatmap may cause some iOS drivers to not drive, changing the composition of drivers online. If these drivers who chose not to drive were also more likely to stay in place or move away from surging areas, then this change in composition could create or accentuate the impact of heatmap invisibility on driver movement toward surge.

We partially control for the impact of driver composition on movement through the inclusion of driver age and driver tenure as covariates. Thus, if present, any impact of this alternate mechanism would need to occur through the portion of its change in composition that is orthogonal to these covariates, or through nonlinear effects of these covariates on movement.

To test the plausibility of this alternate mechanism, we conducted a DID analysis of heatmap invisibility's impact on hours driven. We see an effect that is significant at the 95% level in 3 out of 10 cities.

5 Results

5.1 Impact of Surge on Driver Movement

Maximum likelihood estimates along with confidence intervals for model coefficients are listed in Table 3. This table consists of two parts i) coefficients described in (3) that represent the disutility of moving away from the current hexagon when $\Delta p(t, i, j) = 0$; and ii) coefficients described in (2) that represent the sensitivity of movement to the surge gradient $\Delta p(t, i, j)$.

The table leads to several conclusions. First, it shows that in all cities, drivers incur a disutility for driving out of the current hexagon ($\beta_0 < 0$). Moreover, if they choose to drive out, they derive a higher utility when they are driving toward hexagons with higher surge values ($\beta_1 > 0$). As the estimated value of β_0 is large and negative compared to the other coefficients in (3), if we compute (3) for another combination of factors the coefficient will remain negative. A similar statement tends to hold for β_1 and (2), although not universally.

Second, surge information impacted driver movement, even when controlling for confounding factors. Lack of visibility of the surge heatmap caused drivers to be less sensitive to surge differences: β_5 is significantly negative for all cities except for Washington D.C. and New Jersey. Without the real-time knowledge of seeing the surge heatmap, iOS drivers had a weaker signal of where to drive.

Table 3 quantifies the exogenous effect (β_5) and endogenous effect ($\beta_1 + \beta_3 + \beta_{15}$) of surge for iOS drivers respectively. Therefore, we can measure the actual value of the real time surge information on movement, out of the total surge-movement effect, as

$$e = \frac{-\beta_5}{\beta_1 + \beta_3 + \beta_{15}}$$

The exogenous effect of the heatmap accounted for 10% to 60% of the movement effect (Figure 5). Consistent with discussion below, the effect is the lowest in the large cities with more experienced drivers and higher surge (New York, Boston, Chicago).

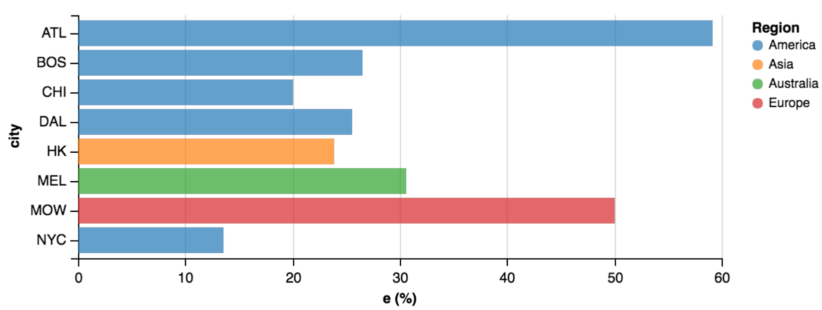


Figure 5: Impact of Surge Information on Movement (%)
Removed Cities with insignificant coefficient (DC, NJ)

Third, in all of the 10 cities, more experienced drivers were less likely to drive out of the current hexagon ($\beta_6 < 0$). Here are two potential explanations: 1) experienced drivers understood that real-time demand conditions may change rapidly, and an imbalance that was causing surge may indeed dissipate in the time it takes to relocate.

For this reason, they chase surge less often than inexperienced drivers; 2) experienced drivers, afraid of being dispatched out of a low-surge hexagon, turned off their *Open* status (go *Offline*) to be indispatchable, then drive toward high-surge hexagon and become *Open* upon arrival. When they were *Open*, they did not need to move further. While experienced drivers moved less often, their movement might be more or less sensitive to the surge values in the direction of movement (β_7). Interestingly, in big cities (Boston, Chicago, Washington D.C.), experienced drivers are less attracted by surge; in small cities (Melbourn, Hong Kong, Moscow and New Jersey), the effect was reversed.

5.2 Impact of Surge on Drivers' Revenue

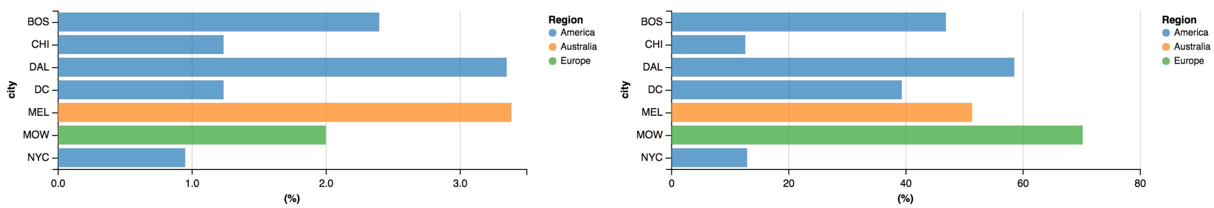
We now ask whether access to the surge heatmap improves drivers' revenue using a similar DID analysis. Specifically, we model driver d's change in hourly revenue from the previous weekend as

$$\text{Revenue}^{\text{outage}}(d) - \text{Revenue}^{\text{previous}}(d) = \alpha_0 + \alpha_1 \cdot \text{iOS}(d) + \alpha_2 \cdot \text{age}(d) + \alpha_3 \cdot \text{tenure}(d) + \eta_d \tag{4}$$

Since iOS drivers were not able to "chase surge" in the outage weekend, we might expect a drop in their revenue compared to Android drivers ($\alpha_1 < 0$). This drop is purely due to the movement activity by utilizing the information on the map, instead of any surge difference on trips at the same dispatched locations. Table 4 summarizes the results of this analysis.

Indeed, iOS drivers earned significantly less in most cities. In the two exceptions (Atlanta and New Jersey), surge constitute less than 3% of all driver revenue during the outage weekend, explaining why no significant difference was detected between iOS and Android drivers' revenue in these two areas.

On average, the absence of surge information reduced driver revenue by 20 to 80 cents per hour for iOS drivers relative to what they would have earned on the outage weekend if their surge heatmap had been visible. This amount does not seem striking, constituting only 1% to 4% of drivers' total revenue (Figure 6a). However, recall: 1) the outage did not change the surged revenue the drivers could obtain; 2) surged revenue only constituted 2% to 12% of all driver revenue, i.e., 40 cents to $3 per hour depending on the city. In fact, dividing the revenue difference (α_1) due to the outage by the total surged revenue, we can calibrate the effects of self-positioning on surge revenue, which ranges from 10% to as high as 70% (Figure 6b). The absence of the heatmap reduced driver revenue in the small cities the most, possibly because these drivers had less experience and they relied more heavily on the heatmap to make positioning decisions.



(a) total driver revenue (b) surged driver revenue

Figure 6: Effect of self-positioning on total driver revenue (%, left) and surged driver revenue (%, right). Cities with insignificant coefficents (ATL, HK, NJ) have been removed.

6 Conclusions

This paper studies the short-run effect of dynamic pricing on Uber's driver partners' self-positioning decisions and revenue. We first built up a driver positioning model in a Multi-nomial Logit setup. Then we used data on a natural experiment covering 135,800 active drivers over two weekends and performed a difference-in-differences estimation that resolved endogeneity issues. The results suggest drivers rely heavily on the real-time dynamic pricing information to make self-positioning decisions, and the effect is lower (10% 30%) in big cities with professional drivers and higher (30% -60%) in small cities and with less experienced drivers. By utilizing this information, drivers can identify potential earning opportunities and significantly improve their surged revenue by up to 70%.

The results imply strong evidence that dynamic pricing is useful as a real-time signaling tool for drivers to make self-positioning decisions that align with rider demand, reducing frictions in the ride-sharing labor market and better coordinating drivers' locations with riders' desire to take trips.

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Appendix: DID Model without Driver Metrics

We also included a DID model with fewer predictors. The results are summarized in Table 5. Similarly, the model shows significant effects of the heatmap ($iOS \cdot week \cdot \Delta p$) for all cities except for Washington DC and New Jersey.

DID Model of Two Regular Weekends

Our conclusion of the impact of dynamic pricing on driver movement hinges on Assumption A7 (The Parallel Trend Assumption), i.e., iOS and Android drivers do not exhibit diverse trends in their sensitivity to prices, after controlling for different driver metrics (Age and Tenure). To test this theory, we ran a similar DID analysis over two regular weekends, including the previous weekend in the main analysis (10/22 to 10/24) and the weekend before (10/15 to 10/17).

The results are summarized in Table 6. For almost all cities, the coefficient on $iOS \cdot week \cdot p$ is insignificant at 95% confidence interval with mixed signs. The only exception is New Jersey, which had no significant results in the outage weekend analysis. This could possibly due to random noise, or some experiment running in the city that had different builts in the platforms.

Table 1: Summary Statistics

	City Metrics			Driver Metrics			
	Trips	Surge Percentage	Average Surge	iOS Drivers	iOS Online Hours	Android Drivers	Android Online Hours
NYC	754753	0.16	1.07	35057	17539	34982	18627
BOS	381959	0.13	1.02	8012	8838	7533	9600
CHI	534294	0.19	1.07	11010	11496	13690	11539
DC	478290	0.07	1.01	5279	2251	5293	2550
ATL	215983	0.03	1.01	4769	6512	7902	4198
DEN	152086	0.17	1.13	2794	2684	4026	1996
MEL	214744	0.15	1.05	6465	3891	4002	6104
HK	117862	0.11	1.06	2269	2921	7401	982
MOW	137170	0.07	1.06	1263	5010	6987	1068
NJ	232656	0.08	1.06	8009	4918	7967	3463

This table summarizes city- and driver-level information for November 4-6, 2016 for the 10 cities with the largest trip volume in which an outage occurred. "Surge Percentage" indicate the fraction of trips in which the driver's surge multiplier exceeded 1. "Average Surge" indicates the average value of the surge multiplier over all trips. The columns "iOS Drivers" and "Android Drivers" count the number of drivers whose primary operating system was iOS and Android respectively. Each corresponding "Online Hours" column indicates the number of hours that these drivers spent open, en-route, or on trip during the reported period.

Table 2: Example of Data.

Row	Driver	Time	OS	Current Hexagon	1-Ring Surge Values	Next Hexagon	Age	Tenure
0	Josie	9:00	iOS	a0	(1.0,1.0,1.2,1.2,1.3,1.0, 1.2)	a0	32	2.5
1	Josie	9:01	iOS	a0	(1.2,1.0,1.2,1.3,1.4,1.0, 1.2)	a1	32	2.5
2	Josie	9:02	iOS	a1	(1.2,1.0,1.2,1.3,1.4,1.0, 1.2)	a2	32	2.5
3	Josie	10:25	iOS	a10	(1.8,2.2,1.7,1.6,1.5,1.5, 1.6)	a12	32	2.5
4	Josie	10:26	iOS	a12	(1.8,2.2,1.7,1.6,1.5,1.5, 1.6)	a12	32	2.5
	...	...	...	...	...	...	...	...
5	Mark	10:25	iOS	b38	(1.0,1.0,1.0,1.0,1.0,1.0,1.0)	b39	41	1.2
6	Mark	10:26	iOS	b39	(1.0,1.2,1.0,1.0,1.0,1.0,1.0)	b40	41	1.2
	...	...	...	...	...	...	41	1.2

This table illustrates the data used to conduct our analysis. Each row represents one driver-minute. It includes a unique identifier for the driver (here represented by a first name, but coded as a hexadecimal number in the data); the time with granularity of minutes; the driver's operating system; the driver's location encoded as a hexagon; the surge multipliers in the driver's current and surrounding hexagons; and the hexagon that the driver moved to in the next minute, if any.

Table 3: Driver Movement Results for 10 Largest Cities.

	NYC	BOS	CHI	DC	ATL	DAL	MEL	HK	MOW	NJ
$const$	$\mathbf{-2.94}^{***}$	$\mathbf{-2.46}^{***}$	$\mathbf{-2.48}^{***}$	$\mathbf{-2.64}^{***}$	$\mathbf{-2.44}^{***}$	$\mathbf{-2.71}^{***}$	$\mathbf{-2.73}^{***}$	$\mathbf{-2.52}^{***}$	$\mathbf{-2.69}^{***}$	$\mathbf{-3.11}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
age	-0.00	$\mathbf{-0.17}^{***}$	$\mathbf{-0.10}^{***}$	$\mathbf{0.18}^{***}$	$\mathbf{0.32}^{***}$	$\mathbf{0.69}^{***}$	$\mathbf{1.01}^{***}$	-0.20	$\mathbf{0.20}^{***}$	$\mathbf{1.19}^{***}$
	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.16)	(0.03)	(0.02)
$tenure$	$\mathbf{-0.00}^{**}$	$\mathbf{-0.06}^{***}$	$\mathbf{-0.03}^{***}$	$\mathbf{-0.04}^{***}$	$\mathbf{-0.20}^{***}$	$\mathbf{-0.23}^{***}$	$\mathbf{-0.04}^{***}$	$\mathbf{-0.36}^{***}$	$\mathbf{-0.12}^{***}$	$\mathbf{-0.15}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
$week$	-0.00	$\mathbf{-0.04}^{***}$	-0.00	$\mathbf{-0.12}^{***}$	$\mathbf{-0.06}^{***}$	$\mathbf{-0.16}^{***}$	$\mathbf{-0.14}^{***}$	$\mathbf{-0.05}^{***}$	$\mathbf{-0.02}^{**}$	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
iOS	$\mathbf{0.03}^{***}$	$\mathbf{-0.04}^{***}$	$\mathbf{-0.04}^{***}$	0.00	$\mathbf{-0.13}^{***}$	$\mathbf{-0.03}^{**}$	$\mathbf{0.07}^{***}$	$\mathbf{-0.04}^{***}$	0.01	$\mathbf{0.33}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$age \cdot week$	-0.01	-0.03	-0.01	$\mathbf{-0.05}^{**}$	$\mathbf{0.03}^{*}$	$\mathbf{-0.24}^{***}$	$\mathbf{0.86}^{***}$	0.04	-0.04	$\mathbf{0.11}^{**}$
	(0.01)	(0.04)	(0.02)	(0.02)	(0.01)	(0.04)	(0.03)	(0.24)	(0.03)	(0.03)
$tenure \cdot week$	0.00	$\mathbf{-0.03}^{***}$	-0.00	-0.01	$\mathbf{-0.02}^{***}$	$\mathbf{0.02}^{**}$	-0.01	0.01	$\mathbf{0.04}^{***}$	$\mathbf{-0.03}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$iOS \cdot week$	-0.01	0.00	$\mathbf{0.03}^{***}$	$\mathbf{-0.04}^{***}$	$\mathbf{0.09}^{***}$	$\mathbf{0.08}^{***}$	0.01	-0.01	-0.01	$\mathbf{0.02}^{*}$
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Δp	$\mathbf{1.25}^{***}$	$\mathbf{1.99}^{***}$	$\mathbf{3.30}^{***}$	$\mathbf{1.97}^{***}$	$\mathbf{2.43}^{***}$	$\mathbf{2.57}^{***}$	$\mathbf{3.20}^{***}$	$\mathbf{1.69}^{***}$	$\mathbf{3.52}^{***}$	$\mathbf{5.61}^{***}$
	(0.05)	(0.04)	(0.07)	(0.07)	(0.09)	(0.12)	(0.09)	(0.08)	(0.08)	(0.35)
$tenure \cdot \Delta p$	-0.04	$\mathbf{-0.11}^{***}$	$\mathbf{-0.36}^{***}$	$\mathbf{-0.23}^{***}$	-0.12	$\mathbf{-0.18}^{*}$	$\mathbf{0.51}^{***}$	$\mathbf{0.65}^{*}$	$\mathbf{0.76}^{***}$	$\mathbf{0.77}^{*}$
	(0.03)	(0.03)	(0.01)	(0.03)	(0.06)	(0.07)	(0.12)	(0.27)	(0.13)	(0.30)
$age \cdot \Delta p$	-0.02	$\mathbf{-2.52}^{***}$	-0.30	0.15	-0.23	-0.16	$\mathbf{3.77}^{***}$	$\mathbf{1.03}^{***}$	-1.44	-0.79
	(0.18)	(0.21)	(0.24)	(0.16)	(0.52)	(0.31)	(0.56)	(0.06)	(0.74)	(1.72)
$iOS \cdot \Delta p$	0.10	$\mathbf{0.18}^{***}$	0.03	-0.04	$\mathbf{0.34}^{*}$	0.24	$\mathbf{0.56}^{***}$	-0.10	$\mathbf{0.44}^{**}$	$\mathbf{-1.15}^{*}$
	(0.06)	(0.05)	(0.07)	(0.07)	(0.16)	(0.17)	(0.10)	(0.15)	(0.16)	(0.53)
$week \cdot \Delta p$	$\mathbf{0.31}^{***}$	$\mathbf{-0.18}^{*}$	$\mathbf{-1.66}^{***}$	$\mathbf{-1.94}^{***}$	-0.10	$\mathbf{1.09}^{***}$	$\mathbf{-0.79}^{***}$	$\mathbf{0.57}^{***}$	0.08	0.36
	(0.07)	(0.08)	(0.09)	(0.07)	(0.15)	(0.13)	(0.10)	(0.12)	(0.11)	(0.71)
$tenure \cdot week \cdot \Delta p$	0.04	0.01	$\mathbf{0.28}^{***}$	0.05	$\mathbf{0.41}^{***}$	$\mathbf{0.26}^{**}$	0.11	-0.45	-0.42	$\mathbf{-0.74}^{*}$
	(0.03)	(0.05)	(0.03)	(0.05)	(0.08)	(0.10)	(0.19)	(0.31)	(0.24)	(0.34)
$age \cdot week \cdot \Delta p$	0.00	$\mathbf{1.44}^{*}$	0.02	$\mathbf{0.62}^{**}$	0.43	0.03	-0.11	$\mathbf{0.97}^{***}$	-1.22	-0.15
	(0.22)	(0.67)	(0.31)	(0.21)	(0.41)	(0.30)	(0.92)	(0.02)	(0.84)	(1.88)
$iOS \cdot week \cdot \Delta p$	$\mathbf{-0.29}^{***}$	$\mathbf{-0.57}^{***}$	$\mathbf{-0.39}^{***}$	-0.08	$\mathbf{-1.45}^{***}$	$\mathbf{-0.95}^{***}$	$\mathbf{-1.05}^{***}$	$\mathbf{-0.72}^{*}$	$\mathbf{-1.03}^{***}$	-0.19
	(0.06)	(0.08)	(0.07)	(0.09)	(0.30)	(0.20)	(0.17)	(0.31)	(0.26)	(0.93)
N	$4.7e6$	$1.7e6$	$2.8e6$	$1.2e6$	$1.1e6$	$5.1e5$	$9.1e5$	$6.8e5$	$6.4e5$	$9.8e5$

*: p-value = 0.05 **: p-value = 0.01 ***: p-value = 0.001

Dependent variables are drivers' hourly earning difference over the two weekends

Table 4: Driver Revenue Results for 10 Largest Cities.

	NYC	BOS	CHI	DC	ATL	DAL	MEL	HK	MOW	NJ
const	0.23	$\mathbf{-5.91}^{***}$	$\mathbf{0.61}^{***}$	$\mathbf{-2.56}^{***}$	$\mathbf{-2.42}^{***}$	0.02	$\mathbf{-5.24}^{***}$	$\mathbf{0.45}^{***}$	$\mathbf{-0.36}^{*}$	−0.22
	(0.22)	(0.26)	(0.18)	(0.17)	(0.20)	(0.31)	(0.33)	(0.09)	(0.15)	(0.18)
iOS	$\mathbf{-0.31}^{*}$	$\mathbf{-0.57}^{***}$	$\mathbf{-0.27}^{**}$	$\mathbf{-0.24}^{*}$	0.06	$\mathbf{-0.61}^{***}$	$\mathbf{-0.75}^{***}$	0.01	$\mathbf{-0.31}^{**}$	−0.03
	(0.14)	(0.15)	(0.10)	(0.10)	(0.12)	(0.18)	(0.19)	(0.06)	(0.10)	(0.21)
age	0.01	$\mathbf{0.63}^{***}$	0.06	$\mathbf{0.14}^{***}$	$\mathbf{0.16}^{***}$	$\mathbf{0.11}^{*}$	$\mathbf{0.90}^{***}$	0.08	0.01	0.07
	(0.03)	(0.06)	(0.04)	(0.03)	(0.04)	(0.05)	(0.07)	(0.12)	(0.03)	(0.07)
tenure	$\mathbf{-0.31}^{***}$	$\mathbf{-1.17}^{***}$	−0.09	$\mathbf{-0.32}^{***}$	$\mathbf{-0.49}^{***}$	$\mathbf{-0.46}^{***}$	$\mathbf{-0.91}^{***}$	$\mathbf{-0.19}^{**}$	$\mathbf{-0.33}^{***}$	−0.17
	(0.07)	(0.08)	(0.05)	(0.05)	(0.07)	(0.10)	(0.15)	(0.07)	(0.07)	(0.18)
N	$3.4e4$	$1.5e4$	$2.7e4$	$2.2e4$	$1.4e4$	$9.4e3$	$9.6e3$	$1.0e4$	$7.8e3$	$2.1e4$

*: p-value = 0.05 **: p-value = 0.01 ***: p-value = 0.001
Dependent variables are drivers' hourly earning difference over the two weekends

Table 5: Driver Movement Results for 10 Largest Cities without Driver Metrics (Appendix)

	NYC	BOS	CHI	DC	ATL	DAL	MEL	HK	MOW	NJ
$const$	$\mathbf{-2.94}^{***}$	$\mathbf{-2.46}^{***}$	$\mathbf{-2.48}^{***}$	$\mathbf{-2.64}^{***}$	$\mathbf{-2.43}^{***}$	$\mathbf{-2.64}^{***}$	$\mathbf{-2.71}^{***}$	$\mathbf{-2.51}^{***}$	$\mathbf{-2.69}^{***}$	$\mathbf{-3.10}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
$week$	0.00	$\mathbf{-0.03}^{***}$	−0.01	$\mathbf{-0.12}^{***}$	$\mathbf{-0.05}^{***}$	$\mathbf{-0.19}^{***}$	$\mathbf{-0.17}^{***}$	$\mathbf{-0.04}^{***}$	−0.01	$\mathbf{-0.01}^{*}$
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
iOS	$\mathbf{0.03}^{***}$	$\mathbf{-0.05}^{***}$	$\mathbf{-0.05}^{***}$	−0.01	$\mathbf{-0.17}^{***}$	$\mathbf{-0.12}^{***}$	$\mathbf{0.10}^{***}$	$\mathbf{-0.06}^{***}$	−0.01	$\mathbf{0.31}^{***}$
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$iOS \cdot week$	−0.01	0.00	$\mathbf{0.03}^{***}$	$\mathbf{-0.03}^{***}$	$\mathbf{0.13}^{***}$	$\mathbf{0.15}^{***}$	0.01	−0.01	0.00	$\mathbf{0.06}^{***}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Δp	$\mathbf{1.28}^{***}$	$\mathbf{2.02}^{***}$	$\mathbf{3.29}^{***}$	$\mathbf{1.80}^{***}$	$\mathbf{2.34}^{***}$	$\mathbf{2.42}^{***}$	$\mathbf{3.41}^{***}$	$\mathbf{1.67}^{***}$	$\mathbf{3.51}^{***}$	$\mathbf{5.86}^{***}$
	(0.04)	(0.03)	(0.06)	(0.10)	(0.16)	(0.18)	(0.13)	(0.09)	(0.12)	(0.34)
$iOS \cdot \Delta p$	0.05	$\mathbf{0.14}^{*}$	−0.10	−0.00	0.39	0.31	$\mathbf{0.58}^{***}$	−0.09	$\mathbf{0.48}^{**}$	$\mathbf{-1.43}^{***}$
	(0.07)	(0.06)	(0.10)	(0.12)	(0.24)	(0.24)	(0.17)	(0.13)	(0.16)	(0.36)
$week \cdot \Delta p$	$\mathbf{0.31}^{***}$	−0.17	$\mathbf{-1.64}^{***}$	$\mathbf{-1.73}^{***}$	−0.06	$\mathbf{1.11}^{***}$	$\mathbf{-1.25}^{***}$	$\mathbf{0.56}^{***}$	0.16	0.20
	(0.05)	(0.10)	(0.07)	(0.11)	(0.33)	(0.23)	(0.17)	(0.15)	(0.15)	(0.53)
$iOS \cdot week \cdot \Delta p$	$\mathbf{-0.24}^{**}$	$\mathbf{-0.63}^{***}$	$\mathbf{-0.31}^{***}$	−0.21	$\mathbf{-1.65}^{***}$	$\mathbf{-1.01}^{***}$	$\mathbf{-0.86}^{***}$	$\mathbf{-0.76}^{**}$	$\mathbf{-0.90}^{***}$	0.41
	(0.08)	(0.16)	(0.09)	(0.13)	(0.48)	(0.24)	(0.19)	(0.25)	(0.18)	(0.56)
N	$4.7e6$	$1.7e6$	$2.8e6$	$1.2e6$	$1.1e6$	$5.1e5$	$9.1e5$	$6.8e5$	$6.4e5$	$9.8e5$

*: p-value = 0.05 **: p-value = 0.01 ***: p-value = 0.001
Dependent variables are drivers' hourly earning difference over the two weekends

Table 6: Driver Movement Results over Two Regular Weekends. (Appendix)

	NYC	BOS	CHI	DC	ATL	DAL	MEL	HK	MOW	NJ
$const$	$\mathbf{-2.80}^{***}$	$\mathbf{-2.55}^{***}$	$\mathbf{-2.53}^{***}$	$\mathbf{-2.71}^{***}$	$\mathbf{-2.62}^{***}$	$\mathbf{-2.54}^{***}$	$\mathbf{-2.63}^{***}$	$\mathbf{-2.55}^{***}$	$\mathbf{-2.69}^{***}$	$\mathbf{-2.84}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
age	-0.01	$\mathbf{-0.07}^{**}$	0.00	$\mathbf{0.15}^{***}$	$\mathbf{-0.15}^{***}$	$\mathbf{0.27}^{***}$	$\mathbf{0.13}^{**}$	$\mathbf{-0.89}^{***}$	$\mathbf{0.25}^{***}$	$\mathbf{0.38}^{***}$
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.21)	(0.06)	(0.02)
$tenure$	$\mathbf{-0.02}^{***}$	$\mathbf{-0.02}^{***}$	$\mathbf{-0.06}^{***}$	$\mathbf{-0.03}^{***}$	$\mathbf{-0.01}^{**}$	$\mathbf{-0.03}^{**}$	$\mathbf{-0.02}^{**}$	$\mathbf{-0.21}^{***}$	0.00	$\mathbf{-0.03}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$week$	$\mathbf{-0.14}^{***}$	$\mathbf{0.10}^{***}$	$\mathbf{0.06}^{***}$	$\mathbf{0.08}^{***}$	$\mathbf{0.19}^{***}$	$\mathbf{-0.10}^{***}$	$\mathbf{-0.05}^{***}$	$\mathbf{0.03}^{***}$	-0.01	$\mathbf{-0.26}^{***}$
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
iOS	-0.00	-0.00	0.01	-0.01	$\mathbf{0.05}^{***}$	$\mathbf{0.09}^{***}$	-0.01	$\mathbf{0.05}^{***}$	0.00	$\mathbf{0.04}^{***}$
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$age \cdot week$	0.00	$\mathbf{-0.12}^{***}$	$\mathbf{-0.11}^{***}$	$\mathbf{0.03}^{*}$	$\mathbf{0.47}^{***}$	$\mathbf{0.41}^{***}$	$\mathbf{0.89}^{***}$	$\mathbf{0.70}^{***}$	-0.05	$\mathbf{0.79}^{***}$
	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.04)	(0.05)	(0.19)	(0.07)	(0.04)
$tenure \cdot week$	$\mathbf{0.01}^{***}$	$\mathbf{-0.04}^{***}$	$\mathbf{0.03}^{***}$	$\mathbf{-0.01}^{*}$	$\mathbf{-0.19}^{***}$	$\mathbf{-0.19}^{***}$	$\mathbf{-0.03}^{**}$	$\mathbf{-0.16}^{***}$	$\mathbf{-0.12}^{***}$	$\mathbf{-0.12}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$iOS \cdot week$	$\mathbf{0.03}^{***}$	$\mathbf{-0.04}^{***}$	$\mathbf{-0.05}^{***}$	0.01	$\mathbf{-0.18}^{***}$	$\mathbf{-0.11}^{***}$	$\mathbf{0.08}^{***}$	$\mathbf{-0.09}^{***}$	0.01	$\mathbf{0.29}^{***}$
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Δp	$\mathbf{1.14}^{***}$	$\mathbf{2.02}^{***}$	$\mathbf{2.86}^{***}$	$\mathbf{2.21}^{***}$	$\mathbf{2.62}^{***}$	$\mathbf{2.20}^{***}$	$\mathbf{3.68}^{***}$	$\mathbf{1.71}^{***}$	$\mathbf{2.44}^{***}$	$\mathbf{1.99}^{***}$
	(0.08)	(0.05)	(0.17)	(0.19)	(0.09)	(0.23)	(0.16)	(0.25)	(0.13)	(0.38)
$tenure \cdot \Delta p$	-0.08	$\mathbf{0.15}^{***}$	$\mathbf{0.64}^{***}$	$\mathbf{0.29}^{*}$	$\mathbf{0.59}^{***}$	-0.09	$\mathbf{0.74}^{***}$	0.09	$\mathbf{0.69}^{***}$	$\mathbf{0.84}^{***}$
	(0.08)	(0.05)	(0.18)	(0.13)	(0.13)	(0.18)	(0.12)	(0.41)	(0.19)	(0.20)
$age \cdot \Delta p$	-0.24	$\mathbf{-1.05}^{**}$	$\mathbf{-4.47}^{***}$	$\mathbf{-3.01}^{**}$	-0.44	-0.27	$\mathbf{-7.86}^{***}$	$\mathbf{1.01}^{***}$	$\mathbf{-2.77}^{*}$	-1.33
	(0.36)	(0.34)	(0.81)	(1.07)	(1.22)	(0.14)	(1.38)	(0.18)	(1.11)	(0.77)
$iOS \cdot \Delta p$	-0.00	$\mathbf{0.16}^{*}$	0.45	0.02	0.29	$\mathbf{0.68}^{*}$	-0.12	0.03	$\mathbf{1.06}^{*}$	-0.04
	(0.09)	(0.08)	(0.24)	(0.21)	(0.23)	(0.34)	(0.18)	(0.58)	(0.47)	(0.55)
$week \cdot \Delta p$	0.13	0.04	$\mathbf{0.61}^{**}$	-0.14	-0.04	0.41	-0.09	0.04	$\mathbf{1.16}^{***}$	$\mathbf{3.85}^{***}$
	(0.09)	(0.07)	(0.22)	(0.21)	(0.15)	(0.29)	(0.26)	(0.21)	(0.17)	(0.52)
$tenure \cdot week \cdot \Delta p$	0.03	$\mathbf{-0.28}^{***}$	$\mathbf{-0.95}^{***}$	$\mathbf{-0.50}^{***}$	$\mathbf{-0.79}^{***}$	-0.00	-0.20	0.33	0.00	0.12
	(0.08)	(0.05)	(0.17)	(0.15)	(0.15)	(0.17)	(0.10)	(0.59)	(0.24)	(0.29)
$age \cdot week \cdot \Delta p$	0.26	$\mathbf{-1.46}^{**}$	$\mathbf{3.87}^{***}$	$\mathbf{3.24}^{**}$	0.19	-0.09	$\mathbf{11.69}^{***}$	$\mathbf{1.01}^{***}$	1.76	-0.15
	(0.36)	(0.47)	(1.09)	(1.19)	(1.25)	(0.09)	(1.39)	(0.17)	(1.17)	(0.46)
$iOS \cdot week \cdot \Delta p$	0.06	0.00	-0.36	-0.02	-0.18	-0.13	0.42	-0.09	-0.66	$\mathbf{-1.45}^{*}$
	(0.11)	(0.11)	(0.25)	(0.20)	(0.32)	(0.26)	(0.30)	(0.54)	(0.55)	(0.72)
N	$3.8e6$	$1.1e6$	$2.2e6$	$1.6e6$	$6.8e5$	$3.2e5$	$5.2e5$	$6.1e5$	$4.2e5$	$7.5e5$

*: p-value = 0.05 **: p-value = 0.01 ***: p-value = 0.001
Dependent variables are drivers' hourly earning difference over the two weekends

Table 7: Driver Supply Hours for 10 Largest Cities

	NYC	BOS	CHI	DC	ATL	DAL	MEL	HK	MOW	NJ
const	$\mathbf{-1.35}^{***}$	$\mathbf{-0.73}^{***}$	$\mathbf{-0.95}^{***}$	−0.16	−0.35	−0.32	$\mathbf{-1.03}^{***}$	$\mathbf{-0.85}^{***}$	$\mathbf{-1.60}^{***}$	−0.09
	(0.13)	(0.19)	(0.14)	(0.15)	(0.21)	(0.25)	(0.25)	(0.23)	(0.44)	(0.06)
os	$\mathbf{-0.42}^{***}$	−0.15	0.03	−0.05	−0.06	−0.15	$\mathbf{-0.33}^{*}$	0.05	$\mathbf{-0.65}^{*}$	−0.14
	(0.08)	(0.11)	(0.08)	(0.09)	(0.12)	(0.14)	(0.14)	(0.16)	(0.29)	(0.07)
age	$\mathbf{0.05}^{*}$	$\mathbf{0.08}^{*}$	$\mathbf{0.06}^{*}$	$\mathbf{-0.06}^{*}$	−0.06	−0.07	0.07	−0.11	0.01	$\mathbf{-0.09}^{***}$
	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.31)	(0.09)	(0.02)
tenure	$\mathbf{0.17}^{***}$	−0.06	−0.02	$\mathbf{0.12}^{**}$	$\mathbf{0.20}^{**}$	$\mathbf{0.22}^{**}$	−0.03	0.04	0.18	$\mathbf{0.14}^{*}$
	(0.04)	(0.05)	(0.04)	(0.04)	(0.07)	(0.08)	(0.12)	(0.17)	(0.21)	(0.06)
N	$3.4e4$	$1.5e4$	$2.7e4$	$2.2e4$	$1.4e4$	$9.4e3$	$9.6e3$	$1.0e4$	$7.8e3$	$2.1e4$

*: p-value = 0.05   **: p-value = 0.01   ***: p-value = 0.001

Dependent variables are drivers' hourly earning difference over the two weekends