Driving the Drivers: Algorithmic Wage-Setting in Ride-Hailing

Yanyou Chen, Yao Luo, Zhe Yuan *

This Version: *August 12, 2023*

Abstract

Firms can now use algorithms to regulate workers' time and activities more stringently than ever before. Using rich transaction data from a ride-hailing company in Asia, we document algorithmic wage-setting and study its impact on worker behavior. The algorithm profiles drivers based on their working schedules. Our data show that drivers favored by the algorithm earn 8% more hourly than non-favored drivers. To quantify the welfare effects of such preferential algorithms, we construct and estimate a two-sided market model with time-varying demand and dynamic labor supply decisions. Results show that removing the preferential algorithm would, in the short term, reduce platform revenues by 12% and total surplus by 7%. In the long run, raising rider fares re-balances demand and supply, resulting in minimal welfare loss. Without the preferential algorithm, an additional 10% of drivers would switch to flexible schedules. Lastly, young, male, local drivers benefit more from the non-preferential algorithm.

Keywords: Two-Sided Market, Fair Pay, Work Schedule, Cross-Time, Elasticity of Labor Supply, Market Power, Compensation Structure

*Contact: Chen: University of Toronto, yanyou.chen@utoronto.ca; Luo: University of Toronto, yao.luo@utoronto.ca; Yuan: Zhejiang University, yyyuanzhe@gmail.com. We are grateful to Victor Aguirregabiria, Heski Bar-Isaac, El Hadi Caoui, Chiara Farronato, Kory Kroft, and seminar participants at the Canadian Economic Association, China-VIOS, NBER SI Digitization, Vanderbilt University, University of Toronto, and University of Western Ontario for helpful discussions and comments. We thank Duoyi Zhang, Anna Li, Mohaddeseh Heydari Nejad, Isaac Shiying Xi, and Weiyue Zhang for excellent research assistance. All errors are our own.

1 Introduction

Recent years have witnessed the rapid acceleration of algorithmic technologies. In labor markets, algorithmic scheduling and wage-setting approaches have spread and changed the relationship between workers and employers. Employers collect a wide array of information on workers to help manage the workforce, direct tasks, and set wages. As a result, firms can now use algorithms to regulate workers' time and activities more stringently than ever before. While algorithms can be designed to be neutral to specific demographics, such as gender, race, or certain age groups, they could evolve into evaluating highly correlated factors, such as work schedules. Gig workers are becoming increasingly aware that their bosses are algorithms that prioritize some objectives that may counteract schedule flexibility.[1] Despite the difficulty in determining the evolution of algorithmic technologies, policymakers and academics are becoming increasingly concerned with the issues that arise in their applications. Economists have just started to examine how algorithms affect market outcomes. For example, Assad, Clark, Ershov and Xu (2020) studies the association between algorithmic pricing and competition. However, few have looked at the labor implications in the design of platforms that automate the management and coordination of workers. Thus, there is an urgent need to better understand the emerging challenges posed by algorithmic technologies in the labor market.

A prominent example is ride-hailing markets. The proliferation of smartphones and mobile internet is driving the global demand for ride-hailing services. A ride-hailing platform provides riders with an economical mode of transportation, such as for daily work commutes, and allows drivers to create their own work schedules to best fit the job into their lives. It is well documented in the literature that workers value alternative work arrangements (Mas and Pallais, 2017). In the ride-hailing industry, Chen, Rossi, Chevalier and Oehlsen (2019) shows that work schedule flexibility increases driver utility. Moreover, geolocation-based matching of drivers and riders creates substantial efficiency gains (Liu, Wan and Yang, 2019). However, work schedules are not treated equally by the platform: some yield more revenue. Information from drivers, including work schedules, is used in profiling and automated decision-making.[2] Inevitably, an optimizing algorithm rewards "high-performing" drivers who work long and consecutive hours for the benefit of the platform. However, due to the lack of information on proprietary algorithms thus far, we have a limited understanding of how algorithms affect market outcomes. Our paper aims to provide the first empirical

[1] The documentary The Gig Is Up (2021) reveals how gig work promised freedom for workers but delivered lower wages and poor working conditions.

[2] Between 2019 and 2022, multiple lawsuits were filed against ride-hailing platforms in the US and Europe to gain access to their secret algorithms. See, e.g., Uber Drivers Sue to Gain Access to its Secret Algorithms.

study of algorithmic wage-setting and its impact on worker behavior and welfare.

First, we argue that ride-hailing companies exercise algorithmic preferential wage-setting, limiting driver utilization of schedule flexibility. Hourly earnings depend not only on the particular hour but also on whether the driver works in other hours. Our arguments highlight one important channel the literature has overlooked: the platform balances demand and supply through the *cross-time* elasticity of substitution in labor supply. Most platforms apply surge pricing to balance demand and supply, which leverages *real-time* labor supply elasticity, by increasing prices when demand exceeds supply. However, surge pricing may discourage demand and reduce transactions if demand is overly elastic. Through implementing a preferential algorithm, the platform can avoid paying high incentive wages when the demand is overly elastic. Instead, the platform can reward drivers when demand is less elastic—relying on such algorithms, platforms profit from maximizing total transactions. Because drivers care about the total of selected values, algorithms can set differential wage rates based on the driver's overall work schedule. Thus, with a preferential algorithm, even in hours when outside options are more attractive, some drivers may still prefer to work because they are rewarded in other hours. As a result, algorithms leverage cross-time labor supply elasticity to increase labor supply in hours with driver shortages. We provide a simple example in Section 2 to sharpen the intuition.

Second, we document significant wage differentials due to work schedules using rich transaction data from one leading ride-hailing company in Asia. We show that three main factors drive the wage differential: high-performing drivers are given more ride requests per hour, wait fewer minutes for each request, and receive more requests from riders with lower cancellation rates. Next, we examine several alternative explanations documented in the literature for the US ride-hailing markets (see, e.g., Cook, Diamond, Hall, List and Oyer, 2021). We rule out alternative explanations of the wage differentials, such as drivers strategically choosing where to work, strategically accepting or canceling orders, driving faster, and having better knowledge of routes. The large wage differential we identify is predominantly due to algorithmic wage-setting, which penalizes low-performing drivers.

Third, we construct and estimate a dynamic model of drivers' hour-by-hour labor supply in a day to quantify the welfare effects of algorithmic preferential wage-setting. We propose a dynamic equilibrium model of a ride-hailing market similar to Frechette, Lizzeri and Salz (2019). We further incorporate decisions of the platform in the two-sided market. Our model accounts for riders' downward-sloping demand, drivers' dynamic labor supply, and the platform's fare and wage setting. Two market power sources drive the platform's pricing decisions: the driver faces alternative time-varying outside options, and the rider has alternative modes of transportation. Drivers first choose work schedule types and then hourly work schedules by solving finite-horizon dynamic discrete choice problems. While drivers can set their own work schedules, the platform rewards high-performing drivers by assigning them more frequent and rewarding trips, leading to wage differentials between work schedules. Combining the estimated labor supply model and the rider demand model, we show how the platform leverages cross-time elasticity using the preferential algorithm. When ride fares are fixed in the short term, eliminating the preferential algorithm will decrease labor supply, resulting in driver shortages for most hours. Our results show that the relation between wage differentials and labor shortages is not one-to-one. Instead, the platform smooths out the payment of high incentive wages by leveraging the cross-time elasticity difference.

Next, we show the welfare effects of eliminating the preferential algorithm. In the short term, eliminating the preferential algorithm will result in drastic loss for both the platform and the riders. On the other hand, the drivers will enjoy more flexibility in choosing a work schedule under "fair" pay. In aggregate, platform revenues will decrease by 12.16%, and total surplus will decrease by 7.16%. The proportion of high-performing drivers will decrease by 11.48% as more drivers switch to being lower performing. For the switchers, the driver surplus will increase by 3.51%. In the long term, the platform will re-optimize its pricing strategy, increasing ride fares to mitigate the short-term driver shortage. As a result, the losses suffered by the platform and riders will be smaller in the long term compared to the short term, resulting in a total decrease in surplus of 1.42%. We also look at how different driver demographics are affected if we eliminate the preferential algorithm. We find that female and older drivers who choose to be high-performing are more likely to suffer from the policy change. The effect for female drivers in general is ambiguous, because women are also more likely to be low-performing drivers, who receive a larger welfare gain from eliminating the preferential algorithm. Non-locals are more likely to suffer a welfare loss if we eliminate the preferential algorithm, because they are more likely to be high-performing. Lastly, we investigate what factors determine the effectiveness of the preferential algorithm. We conduct counterfactuals by alternating key structural parameters. We find that the platform benefits more from implementing a preferential algorithm when rider demand is more elastic or when warm-up cost is greater. Meanwhile, the loss of driver surplus with a preferential algorithm is smaller when demand is more elastic or the warm-up cost is greater.

Related Literature

Our paper is one of the first to study how algorithms affect market outcomes. Rambachan, Kleinberg, Ludwig and Mullainathan (2020) develops an economic perspective on algorithmic fairness and related issues. Calvano, Calzolari, Denicolo and Pastorello (2020) shows how algorithmic pricing leads to collusive strategies in an oligopoly model of repeated price competition. Assad, Clark, Ershov and Xu (2020) shows that AI adoption has a significant effect on competition by studying Germany's retail gasoline market. Using rich transaction data from one of the leading ride-hailing companies in Asia, we provide the first empirical study of algorithmic wage-setting and its impact on worker behavior and welfare.

Our results add to the labor literature on compensation and incentives in the workplace. Economists have understood the importance of incentives for decades and made good progress in specifying how compensation and its form influence worker effort. See Lazear (2018) for an excellent summary. However, little is known about the compensation and incentives provided by new algorithmic technologies. Our paper provides the first empirical study on how algorithmic wage-setting manipulates the pay structure and alters worker behavior. Such analysis is especially important under the context that there has been a rise in the incidence of alternative work arrangements (Katz and Krueger, 2019). Our results also add to the discussion on wage differentials. There has been extensive documentation of wage differentials based on demographics, such as gender and race. Altonji and Blank (1999) provides a great overview of this literature. Blau and Kahn (2017) surveys the literature on the gender pay gap. Another small literature studies part-time and full-time wage differentials. For example, Aaronson and French (2004) studies the joint determination of hours and wages, exploiting variation in labor hours induced by social security rules. Our paper is the first to document wage differentials due to different hourly work schedules under algorithmic wage-setting.

Some earlier papers have used taxi data to investigate individual labor-supply decisions. Farber (2008) and Crawford and Meng (2011) estimate a structural model of a taxi driver's stopping decision, allowing for reference-dependent preferences. However, they do not analyze the industry equilibrium. Instead, similar to Chen, Ding, List and Mogstad (2020) and Frechette, Lizzeri and Salz (2019), our model studies the overall equilibrium of the ride-hailing market. We estimate a dynamic labor supply model with driver preferences over work schedules. There is a growing literature studying the ride-hailing market. Castillo (2020) studies Uber's surge pricing using an empirical model of the two-sided market with riders, drivers, and the platform. Ming, Tunca, Xu and Zhu (2019) also demonstrates that surge pricing improves rider and driver welfare as well as platform revenues. Instead of surge pricing, our paper highlights another important channel: the platform balancing of demand and supply through the *cross-time* elasticity of substitution in labor supply by the implementation of preferential algorithms.

Lastly, our empirical strategies follow the empirical industrial organization literature. Our model builds on the literature on two-sided markets, focusing on how the platform sets prices for both sides. See Rysman (2009) for a comprehensive survey. We take this view to the ride-hailing market, allowing for two sources of market power: driver and rider outside options. While Rysman (2004) proposes a general setting with oligopolistic competition between platforms, we focus on one leading platform in Asia. This simplification approximates the industry structure well and allows us to incorporate important dynamics in drivers' labor supply. In estimating rider preferences, we employ an IV approach, similar to Kalouptsidi (2014), to deal with unobserved factors that may affect demand and rider fare schedules. In estimating drivers' preferences, we propose a GMM estimator that integrates the CCP estimator of Hotz and Miller (1993). We also account for driver unobserved heterogeneity in estimating the structural parameters in their dynamic discrete choice.

The remainder of the paper is organized as follows. Section 2 proposes a motivational example to explain why the platform has incentives to implement a preferential algorithm. Section **??** describes the ride-hailing industry in Asia and our data. Section 4 provides reduced-form evidence of algorithmic wage-setting that favors high-performing drivers. Moreover, we conduct robustness analysis to exclude alternative explanations. Section 5 describes an equilibrium model with a dynamic model of drivers' labor supply. Section 6 discusses our estimation results, and Section 7 discusses our counterfactual experiments. Section 8 concludes. The Appendix contains all omitted details.

2 Preferential Algorithm

Worldwide, online platforms are accused of implementing preferential algorithms to restrict the work flexibility of gig workers. For example, Uber Eats' algorithm gives preference to full-time workers over part-time workers when assigning orders. Similarly, DoorDash's algorithm discourages gig workers from strategically choosing orders. If a worker declines a delivery order that would take them approximately 12 km away, they may stop receiving further delivery requests. Furthermore, there are claims that Instacart exercises significant control over the labor process thereby restricting workers' autonomy over their time and the work they can undertake.[3] Our paper aims to understand what precisely a preferential algorithm does and why such an algorithm is employed by platforms. Specifically, we study one of the leading ride-hailing platforms in Asia, which we refer to as "Platform X" to maintain confidentiality.[4] Platform X's algorithm grants preferential order assignment to drivers based

[3]The news report for Uber Eats: Uber gets almost everything it wants in Ontario's Working ForWorkers Act; DoorDash: Apps like Uber and DoorDash use AI to determine pay. Workers say this makes it impossible to predict wages. Instacart: At The Mercy Of An App: Workers Feel The Instacart Squeeze.

[4]The leading ride-hailing platforms in Asia include Uber, Lyft, Didi, Grab, Gojek, Ola, among others. With the development of Asia's residential travel demand, the number of ride-hailing users in Asia grew to

on their total working hours, particularly during incentivized hours. Below, we elaborate on how Platform X's preferential algorithm works in detail.

2.1 Preferential Algorithm in Ride-Hailing

Platform X typically distributes requests to drivers within three kilometers. Within this designated radius, Platform X gives priority to particular drivers based on their order assignment scores. Drivers earn points based on the time they spend and the duration they work for the platform. In the city we are investigating (as of 2018), Platform X's fare schedules segment a workday into six intervals. (1) morning 7:00-10:00, (2) midday 10:00-16:00, (3) afternoon 16:00-19:00, (4) evening 19:00-22:00, (5) night 22:00-00:00, and (6) early-morning 00:00-6:59 (next day). The points earned per hour for drivers vary depending on the specific time intervals. Certain intervals are designated as incentivized hours, during which drivers receive higher points for their work. In the app, drivers have access to the points earning formula, which provides them with precise information about the number of points they will earn at different times of the day. On average, drivers earn 0.3 points for each order they fulfill. The total score of a driver is computed by summing up all the points they have earned during the previous thirty days.

Figure 1 presents the information visible to the drivers.[5] The driver is presented with their current score, which in this case is 236.6. Subsequently, there is a line indicating the percentile of their score, stating that the score is "better than 66% of drivers in the same city". At the bottom of the screen, there is a line that explains the usage of the score to the drivers, stating that "the higher the score, the higher priority you will have in order assignment." To summarize, drivers are provided with the formula for earning points, possess full knowledge of their current score, and also understand that the score directly impacts the priority of order assignment.

Regarding the fare schedules, all the drivers face the same fare schedules on Platform X. Thus, hourly wage differentials across drivers mainly come from systematic differences in order assignment. Riders pay a 10 CCY base fare, 0.38 CCY per minute, and 1.9 CCY per mile for each Platform X Express trip. During the morning hours (7:00-10:00), the per-mile rate increases to 2.5 CCY, and during the afternoon (16:00-19:00), night (22:00-0:00), and early-morning (0:00-7:00) hours, the per-mile rate is 2.4 CCY. Drivers receive 79.1% of the

800 million by the end of 2020. Platform X has millions of ride-hailing drivers and serves over one hundred million people globally, collecting an annual revenue of over $10 billion USD in 2020. Platform X offers several tiers of operations: express, premium, and luxury. Our study focuses on its express service. Like UberX in the U.S., express accounts for most of the service provided on Platform X in Asia.

[5] Due to confidentiality reasons, we exclude all specific firm information. Instead, we present a generic illustration that precisely replicates the information displayed to drivers on the platform.

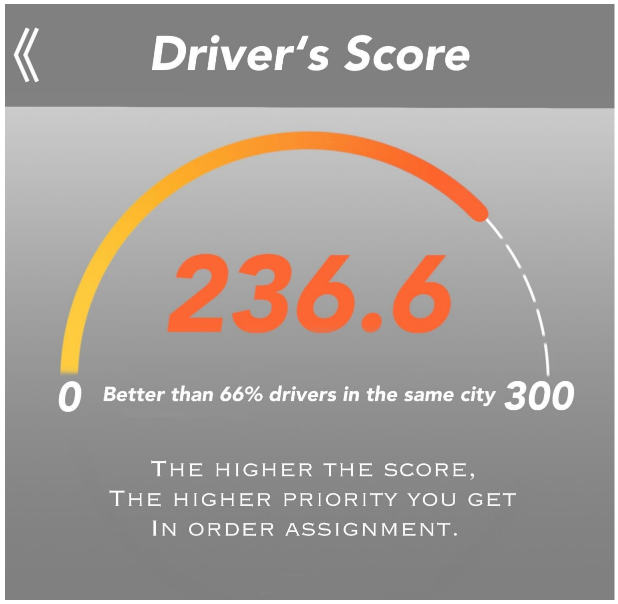


Figure 1: Information Displayed to Drivers

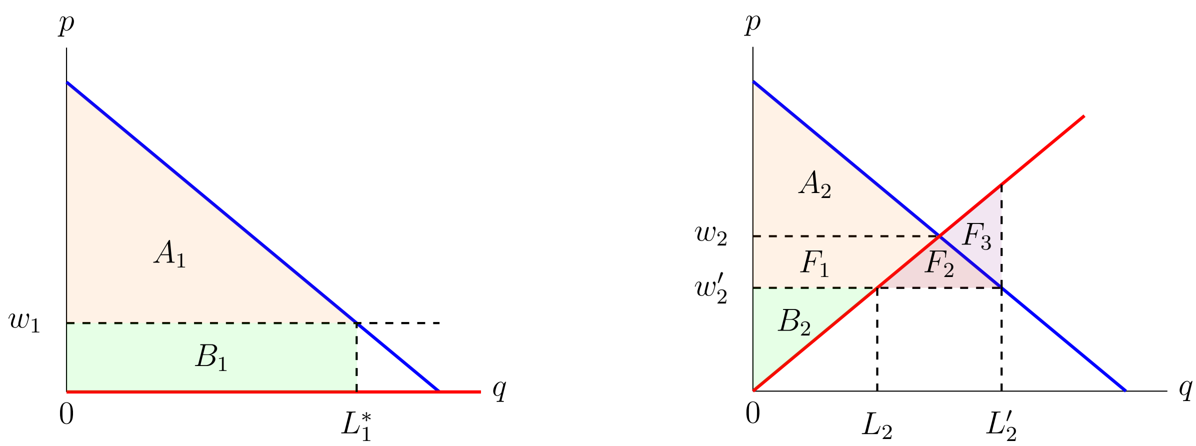
rider fare.[6]

2.2 Why Implementing a Preferential Algorithm

We will now elaborate on why the platform has a motivation to introduce a preferential algorithm. First of all, if the platform can apply first-degree price discrimination to both consumers and drivers, it can maximize its profit to the fullest extent. In such a scenario, the platform captures the entire surplus from both consumers and drivers, and introducing a preferential algorithm will not increase the platform's profit. The preferential algorithm is effective only in situations where the platform cannot achieve perfect price discrimination among drivers. In reality, the platform may be able to extract consumer surplus through mechanisms like surge pricing. However, extracting the entire surplus from drivers is challenging due to factors such as labor laws or the design of the wage scheme. For instance, in countries like France, there are regulations requiring a minimum payment for drivers per ride, resulting in a surplus for drivers.

Figure 2 presents a scenario where the implementation of a preferential algorithm is profitable for the platform. Panel (a) and (b) represent two distinct time periods, t_1 and t_2. In both periods, the platform captures the entire consumer surplus by employing surge pricing, while providing drivers with a constant wage throughout each time period. The red line represents the labor supply curve in each time period, while the blue line represents

[6] The information is obtained from Platform X's annual report.



(a) t_1 with excessive labor supply

(b) t_2

Figure 2: Cross-Time Elasticity Differentials

the demand curve. Assuming, without loss of generality, that the alternative outside option for drivers has a value of zero at t_1. At time period t_1, the platform compensates drivers with a wage rate of w_1, leading to a surplus of B_1 for the drivers. The platform is unable to further decrease wage rate at t_1 because of minimum wage requirement. At t_1, there is an abundance of drivers willing to work at the wage rate w_1. However, in equilibrium, only L_1^* drivers are able to receive orders and earn a surplus. The platform has the authority to select which drivers among the available pool will receive orders. This ability to choose drivers necessitates the implementation of a preferential algorithm, which the platform utilizes to extract additional surplus from the drivers.

Without a preferential algorithm, the equilibrium wage rate at t_2 is w_2, determined by the point of intersection between the demand and supply curves. At time period t_1, the platform earns a profit of A_1, while at time period t_2, it earns a profit of A_2. Therefore, the total profit for the platform in the absence of a preferential algorithm is $A_1 + A_2$, while the driver surplus amounts to $B_1 + B_2 + F_1$.

With a preferential algorithm, the platform communicates to drivers that if they work during time period t_2, they will be given priority and receive an order during time period t_1. Hence, the platform can motivate drivers to work during time period t_2 without offering substantial incentive wages. As a result, the platform can lower the wage rate to w_2' during time period t_2 and still sustain the desired level of labor supply, denoted as L_2'. Therefore, with the implementation of a preferential algorithm, the total profit for the platform becomes $A_1 + A_2 + F_1 + F_2$, and the driver surplus is calculated as $B_1 + B_2 - F_2 - F_3$.

Typically, the platform needs to offer high incentive wages to motivate drivers to work more. For instance, at the wage rate w_2' during t_2, if the platform intends to increase the labor supply from L_2 to L_2', it would need to provide additional compensation of $F_2 + F_3$ to motivate additional drivers to work. Nevertheless, with the implementation of a preferential algorithm, the platform no longer needs to offer such incentive wages. Instead, the platform can prioritize drivers who work during time period t_2 for order assignment during time period t_1. Drivers who choose to work at t_2 are now compensated by earning a surplus during t_1. The power of implementing a preferential algorithm lies in the presence of an excess supply of drivers during time period t_1 and the platform's ability to select which drivers will receive orders in such situations. The effectiveness of the preferential algorithm depends on the disparity in demand and labor supply elasticity across different time periods, which we refer to as cross-time elasticity differentials.

The simple theoretical model presented here highlights the incentive of using a preferential algorithm. The preferential algorithm serves as a means for the platform to extract additional driver surplus in situations where it is unable to conduct first-price discrimination for drivers. The preferential algorithm leverages cross-time elasticity differentials to extract additional driver surplus, while surge-pricing utilizes real-time elasticity to maximize the platform's profit. Despite their different mechanisms, the platform achieves higher profit from both surge-pricing and the preferential algorithm. In Appendix A, we use our theoretical model to illustrate the contrasting ways surge-pricing and the preferential algorithm operate, as well as to highlight their potential complementarity. Specifically, we conduct a comparison of the equilibrium outcomes in four scenarios: without surge-pricing and the preferential algorithm, with only surge-pricing, with only the preferential algorithm, and with both surge-pricing and the preferential algorithm.

3 Data

To study the wage differential resulting from the preferential algorithm, we acquire transaction-level data from the Transportation Bureau of a major city in Asia. We observe all the completed transactions of all ride-hailing platforms in December 2018 for that city.[7] We also observe drivers' attributes such as age, gender, and birth location.

For each transaction, we observe the trip's origin, destination, and distance, as well as the duration spent on passenger pickup and transportation, and the corresponding payment received by the driver. The transaction-level data allows us to observe the detailed work schedules of the drivers and detailed information on the orders they received. Furthermore, the order details encompassing origin, destination, wait time, pick-up time, and drive time

[7] The city we study has a population of around eleven million.

enable us to assess the quantity and quality of orders received by different drivers. Therefore, we can investigate the underlying factors contributing to drivers' wage differentials. One caveat is that while we have data on completed transactions from all ride-hailing platforms, our main analysis focuses only on Platform X. We focus our main analysis on Platform X for two key reasons. Firstly, Platform X holds a dominant position in the city under study, accounting for more than 90% of the market share. Secondly, our data indicates that drivers rarely multi-home or switch between different platforms, suggesting that platform competition is almost negligible in our city of study.[8] As a result, we focus on Platform X as the primary subject of our analysis.

Table 1 summarizes our data set. The unit of observation is at the driver-hour level.[9] A driver serves, on average, 1.9 orders per hour and earns 50 CCY. The number of orders ranges from 1 to 9 between the 25$^{\text{th}}$ percentile and the maximum value, demonstrating a significant variation in the number of orders fulfilled by drivers within an hour. For each hour worked, drivers generally only spend half the time transporting riders. On average, drivers spend 10 minutes picking up riders and another 19 minutes waiting for orders. Considering that a substantial amount of time is spent in picking up riders and waiting for orders, having a higher priority in order assignment plays a significant role in improving a driver's hourly wage.

Table 1: Summary Statistics (Driver-Hour)

	Mean	Std. Dev.	Min	25 Pctl	Median	75 Pctl	Max
Hourly Wage (CCY)	49.98	24.52	0	32.83	47.42	62.74	286.86
Earning Time (minutes)	30.60	12.01	0	21	31	40	60
Pickup time (minutes)	10.62	6.67	0	6	10	15	60
Idle Time (minutes)	18.78	14.32	0	6	17	29	60
Number of Orders	1.89	1.11	0	1	2	3	9
Distance (km)	14.11	7.41	0	8.78	13.1	18.2	94.13
Number of Observations				4,182,318			

Table 2 summarizes the driver characteristics. There are 40,104 unique drivers in our data, among which 2.7% are female drivers, and 37.4% are local drivers. We define local drivers as drivers with local household registration permits.[10] Household registration permits

[8]Appendix F shows a detailed analysis regarding multi-homing.

[9]The unit of observation in our raw database is at the driver-rider-order level. We primarily concentrate on weekdays (a total of 21 days) due to variations in supply, demand, and fee schedules between weekdays and weekends. Following the literature, we conduct our main demand estimation and counterfactual analysis at the driver-hour level. For more details on how we derive the driver-hour level data from the raw data, please refer to Appendix E.

[10]Household registration permits are issued by the government, and indicate the particular area a person

have a profound impact on residents' capacity to buy houses, access schools and childcare facilities, thereby influencing their available opportunities in the job market. Table 2 shows that drivers work a median of 13 days out of the 21 workdays. There is considerable heterogeneity across the number of days each driver works, ranging from 5 to 19 days between the 25th and 75th percentiles. Moreover, there is substantial variation in the number of work hours per day, with the 25th percentile driver working 4.8 hours, while the 75th percentile driver works for 10.5 hours.

Table 2: Summary Statistics of Driver Characteristics

Characteristic	Mean	Std. Dev.	Min	25 Pctl	Median	75 Pctl	Max
Age	37.29	8.24	21	31	37	43	61
Work Days	12.02	7.03	1	5	13	19	21
Daily Work Hours	7.61	3.59	1	4.75	8.09	10.47	18

Compared to Uber data from the US market, the summary statistics of drivers working for Platform X in our city of study are substantially different. For instance, according to Cook, Diamond, Hall, List and Oyer (2021), 27.3% of Uber drivers are women. However, just 2.7% of the drivers in our data are female. Additionally, our drivers dedicate significantly more time to their work, averaging around 7.6 hours per day, while Uber drivers usually work approximately 3 hours per day. The substantial difference in working hours may be attributed to the preferential algorithm discussed in this study.

High-Performing and Low-Performing Drivers

Section 2.1 provides a comprehensive explanation of the preferential algorithm used by Platform X. While the platform's assigned driver scores are not directly observable in our data, we can infer the historical driving performance of each driver from the transaction data since we have access to all completed transactions.

We first verify whether working longer hours, particularly during incentivized hours, leads to increased order assignment priority and subsequently higher hourly wages, as exlained in Section 2.1. We regress the hourly wage of a driver on the total number of hours worked in a month and the percentage of incentivized hours worked, controlling for day, hour, and operation area fixed effects. According to the interviews with drivers and engineers at Platform X, during our study period, mid-day and night hours (starting from 7 PM onwards) were identified as incentivized hours. Table 3 shows the results. Generally, drivers who work more, especially during incentivized hours, earn a higher hourly wage than other drivers. Column

is from, in which the registrant is entitled to benefits such as hospitals, schools, or land-purchasing rights.

(2) of Table 3 shows that working one additional hour in a month increases a driver's hourly wage by 0.3 cents. Given that the 25^{th} to 75^{th} percentiles of drivers work 27 to 172 hours, their hourly wage gap is 0.435 CCY or 0.87% of the average hourly wage. A more important feature of higher hourly wages is the fraction of incentivized hours worked. Allocating 1% more of work time to incentivized hours increases hourly wage by 0.187 CCY. Given that the 25^{th} to 75^{th} percentile drivers spend 55% to 72% of their work time on incentivized hours, respectively, their hourly wage gap is 3.2 CCY or 6.4% of the average hourly wage. The findings indicate that the preferential algorithm employed by Platform X aligns with its description. Drivers who put in longer hours and work more during incentivized hours are indeed given priority in order assignments, resulting in a higher hourly wage for them. In Section 4, we thoroughly investigate how the preferential algorithm drives this wage differential and eliminate alternative explanations.

Table 3: Factors Correlated With Hourly Wage

Hourly Wage	(1)	(2)
# of Work Hours in month	0.003***	0.003***
	(0.000)	(0.000)
% Incentivized Hours		18.724***
		(0.170)
Constant	54.918***	39.201***
	(0.126)	(0.190)
Observations	4,182,331	4,182,331
R-squared	0.040	0.043

Notes: We control for day-hour fixed effects, origin district fixed effects, and destination district fixed effects. Standard errors are in parentheses. *** p<0.01.

One computational challenge arises from the fact that, for each hour, a driver has the option to choose whether to work or not. As a result, the number of potential driver work schedules on any given day reaches 2^{24}. This vast number of possible driver statuses is computationally impractical for our model estimation and counterfactual analysis. Therefore, we explore the possibility of clustering drivers into different types based on their historical working performance to effectively reduce the number of potential driver statuses.

We implement machine learning algorithms to cluster drivers based on their hourly wages, work schedule, and other observed characteristics of drivers.

The findings indicate that we can primarily classify drivers into two distinct types, and this result is robust to various specifications.[11] The first type comprises high-performing

[11] Online Appendix H describes the machine learning algorithm we use to cluster drivers.

drivers, who can also be perceived as committed or full-time drivers. The second type includes low-performing drivers, who can also be perceived as non-committed or part-time drivers. Based on the analysis, we formally classify the two types of drivers as follows: A driver is considered high-performing if they worked for at least two consecutive hours during incentivized hours (midday or night) on a minimum of 8 out of the 21 workdays. Conversely, a driver is classified as low-performing if they do not meet these criteria.[12] Throughout all our subsequent analyses, we use the terms "H-type" and "L-type" to represent the status of drivers as high-performing and low-performing, respectively.

Table 4 summarizes the characteristics of high-performing and low-performing drivers. There are $23,712$ high-performing drivers and $16,392$ low-performing drivers. Panel I reports the drivers' characteristics. High-performing drivers are more likely to be non-local drivers and male drivers. Women account for 2.2% of the high-performing drivers and 3.5% of the low-performing drivers. Non-locals account for 69% of the high-performing drivers and only 53% of the low-performing drivers. The average age is comparable between high-performing and low-performing drivers. Panels II and III report driver performance. On average, high-performing drivers work more, averaging 17 out of 21 workdays, while low-performing drivers, on average, work 5 out of 21 workdays. In any given hour, conditional on working, high-performing drivers have more passenger-service time (30.7 minutes versus 29.3 minutes) and spend less time waiting for orders (18.6 minutes versus 20.4 minutes). High-performing drivers finish more orders (1.9 orders versus 1.74 orders) and earn more (50.4 versus 46.5 CCY per hour) compared to low-performing drivers.

4 Reduced-Form Evidence

In this section, we first provide evidence to show that high-performing drivers earn a higher hourly wage. We then investigate the factors driving the wage differential. Last, we rule out alternative explanations for the observed wage differential between high-performing and low-performing drivers, including strategically choosing where to work, strategically selecting and canceling orders, driving faster, and having a better knowledge of routes.

[12] We performed various robustness checks by changing the threshold of being high-performing drivers. For example, we changed the required number of days from 8 to 9, 10, 11, etc., out of 21 workdays; we put further restrictions on the total number of hours worked per month at various levels. Reduced-form results in Section 4 are robust to these definitions. As explained in the main context, the key feature of high-performing drivers is the percentage of hours worked consecutively in incentivized hours. Because of the high fixed cost of starting to work, consecutively worked hours during incentivized hours are highly correlated with the total number of hours worked. This may help explain why the two criteria we use in the main context are robust to all the variations mentioned here.

Table 4: High/Low-performing Driver Characteristics

	High-performing (1)	Low-performing (2)
Panel I: Driver/Vehicle Characteristics		
% femal	2.2%	3.5%
% non-local	69%	53%
Age	37.2	37.4
Panel II: Performance (in a month)		
Work Days	17	5
Work Hours	159	26
# of orders	301	46
Monthly Revenue	7,985	1,202
Panel III: Performance (in an hour)		
Work Time	30.7	29.3
Pickup time	10.7	10.2
Idle Time	18.6	20.4
# of orders	1.90	1.76
Hourly Revenue	50.4	46.5
# of drivers	23,712	16,392
Share of Drivers	59.1%	40.9%

4.1 Wage Differential

First, conditional on working in the same hour, we test whether high-performing drivers earn more compared to low-performing drivers. We regress the hourly wage of a driver on an indicator of being high-performing and controlling for day-hour, origin, and destination fixed effects. Table 5 shows a significant difference in hourly wage between high-performing and low-performing drivers. High-performing drivers earn 3.8 CCY or 8.2% more hourly than their low-performing counterparts. The result is very robust, with or without controlling for various fixed effects.[13]

Given that high-performing drivers earn significantly higher hourly wages, we investigate what factors drive the wage differential. We study the characteristics of orders that high-performing and low-performing drivers receive. For example, we evaluate the average distance of their orders and how often the rider cancels the order. We also compare the number of orders, the amount of idle time, and the time spent serving the customer between the two types of drivers. Table 6 shows the results. Column (1) shows that conditional on working in the same hour, high-performing drivers receive more orders than low-performing

[13]Appendix K reports IV regression results. We show that with changes in Precipitation and Air Quality Index as instrument variables, we find a larger wage gap between high-performing and low-performing drivers.

Table 5: Wage Differential: High-performing versus Low-performing

Dependent Variables	Hourly Wage		
	(1)	(2)	(3)
High-performing	3.886***	3.794***	3.851***
	(0.0397)	(0.0393)	(0.0391)
Constant	46.49***	46.57***	47.24***
	(0.0376)	(0.0372)	(0.0701)
Day-Hour FE		Y	Y
Origin FE			Y
Destination FE			Y
Observations	4,182,328	4,182,328	4,182,328
R-squared	0.002	0.039	0.050

Notes: Standard errors in parentheses. *** p<0.01

drivers. On average, high-performing drivers receive 0.125 more orders or 7.1% more every hour. Second, orders assigned to high-performing drivers are 2.8% less likely to be canceled by riders (column 2).[14] Because high-performing drivers get assigned more orders every hour, they also drive 0.748 more kilometers and 5.4% more time carrying riders in an hour (column 4).[15] More importantly, high-performing drivers spend 10.5% less time waiting for orders (column 5). This result is consistent with our argument in Section **??** that the algorithm prioritizes high-performing drivers for better order assignments.

In summary, Table 6 shows that three main factors are driving the wage differentials between high-performing and low-performing drivers. High-performing drivers are given more rides from the platform, waste less idle time waiting for orders, and receive more orders from higher quality riders (lower probability of rider-initiated cancellation). As the platform's algorithm determines the assignment of orders, we hereafter term the systematic difference in the quantity and quality of order assignments based on work schedule (high-performing versus low-performing) as algorithmic preferential wage-setting.

[14] Our main analysis throughout this paper uses data on completed transactions. Our data includes information on canceled orders in the first ten days (from December 1st to December 10th, 2018). We use data on completed transactions and canceled orders for all regressions involving cancellation rates. Therefore, the number of observations differs from that of other regressions.

[15] Gaineddenova (2021) shows that drivers prefer more expensive trips with a shorter pickup distance, using data from a decentralized ride-hailing platform.

Table 6: Driving Forces of Wage Differential

Dependent Variables	# Orders	Cancellation Rate (Rider)	Drive Dist	Earning Time	Idle Time
	(1)	(2)	(3)	(4)	(5)
High-performing	0.125***	-0.0023***	0.748***	1.579***	-2.140***
	(0.0018)	(0.0004)	(0.0003)	(0.0187)	(0.0221)
Constant	1.468***	0.0894***	12.85***	32.35***	17.04***
	(0.00313)	(0.0005)	(0.0212)	(0.0334)	(0.0395)
Mean of Low-performing	1.76 (orders)	8.2%	13.4 (km)	29.3 (min)	20.4 (min)
High-performing compared to Low-performing	7.1%	-2.8%	5.6%	5.4%	-10.5%
Observations	4,182,318	4,815,026	4,182,318	4,182,318	4,182,318
R-squared	0.080	0.006	0.045	0.100	0.115

Notes: In all columns except for column (2), we use completed transactions for the analysis. Completed transactions are available from Dec. 1, 2018 to Dec. 31, 2018. In column (2), we also include canceled orders to compute rider cancellation rates. Information on canceled order is available from Dec. 1, 2018 to Dec. 10, 2018. Standard errors are in parentheses. All specifications control for day-hour fixed effects, origin district fixed effects, and destination district fixed effects. *** p<0.01

4.2 Rule Out Alternative Explanations

There could be alternative explanations for the wage differentials between high-performing and low-performing drivers. Rather than having the algorithm prioritize different work schedules when assigning orders, some may argue that drivers make decisions endogenously, resulting in the observed wage difference. For example, Cook, Diamond, Hall, List and Oyer (2021) finds that the gender earnings gap amongst drivers can be entirely attributed to three factors: experience on the platform (learning-by-doing), preferences and constraints over where to work (driven largely by where drivers live and, to a lesser extent, safety), and preferences over driving speed. To provide a robustness check for our findings, we consider four alternative explanations and use our data to prove that such alternative explanations are unlikely to be true in our context. First, high-performing drivers may have better knowledge of the popular rider pickup areas (hot spots) and get more orders. Second, high-performing drivers may learn how to reject and cancel rides strategically. Third, high-performing drivers may drive faster than others and earn a higher hourly rate. Fourth, high-performing drivers may know the streets better and choose better routes than low-performing drivers.

High-Performing Drivers Strategically Choose Where to Work

First, we explore whether high-performing drivers have better knowledge of hot spots, and hence are strategically choosing where to work and earn more hourly.[16] There are eight dis-

[16]For example, Haggag, McManus and Paci (2017) finds that New York taxi drivers accumulate neighborhood-specific experience, which helps to find riders.

tricts in the city we study. We first examine where the high-performing and low-performing drivers work and whether they tend to pick up / drop off clients in different areas. Table 7 suggests no substantial difference between the origin or destination districts where high-performing and low-performing drivers work.

Table 7: Active Area for High-performing and Low-performing Drivers

District	Origin		Destination	
	Low-performing	High-performing	Low-performing	High-performing
1	7%	7%	7%	7%
2	9%	8%	9%	8%
3	20%	22%	21%	23%
4	7%	7%	7%	7%
5	16%	15%	15%	14%
6	10%	11%	10%	11%
7	16%	15%	16%	15%
8	16%	15%	15%	13%
Total	100%	100%	100%	100%

To better control for location-fixed effects, we manually divide the eight districts into even finer 1km $\times$ 1km grids. Because we observe the coordinates of each pick-up and drop-off location, we can accurately place trip origins and destinations into each of the fine grids. Re-running our main regression with day-hour and grid fixed effects, column (2) of Table 8 reports the result, which is close to our main result in column (1).[17] It shows that the wage differential between high-performing and low-performing drivers cannot be explained by high-performing drivers picking up or dropping off passengers from certain locations or neighbourhoods. We further divide each hour into four 15-minute intervals as a robustness check. Instead of controlling for day-hour fixed effects, we control for day-hour-15minute fixed effects. With a finer measure of location and time-fixed effects, we are essentially comparing drivers who work in the same location at the same time. The only difference between the drivers is their performance level, which is determined by their past work schedules. Column (3) reports the result controlling for day-hour-15minute and grid fixed effects, and column (4) reports the result controlling for day-hour-15minute-grid fixed effects. The results in all of the robustness checks are close to our benchmark result in column (1). Thus, knowledge of hot spots and strategically choosing where to work is an

[17] Column (1) of Table 8 is identical to column (3) of Table 5, where we control for origin, destination, and day-hour fixed effects.

unlikely explanation for the wage differential between high-performing and low-performing drivers.

To mitigate potential biases in driver selection based on unobservable characteristics, we have employed instrumental dummy variables: the rate of change in precipitation and air quality index (AQI) in the driver's hometown city between 2017 and 2018. The selection of drivers based on these variables is not influenced by the drivers' unobserved characteristics. These weather variables satisfy the two conditions required for valid instrumental variables (IVs). Firstly, the occurrence of precipitation and changes in air pollution may be correlated with a driver's decision to become a high-performing driver, as suggested by (Miguel et al., 2004). For instance, alterations in precipitation and air pollution might motivate more drivers to leave their hometowns and become high-performing drivers in the focal city under study. Secondly, the variation in weather conditions in a driver's hometown should not directly impact the driver's hourly rate or order distribution in the city being studied. The IV results are presented in column (5), revealing a more significant wage differential between high-performing and low-performing drivers. For further details and additional IV results, please refer to Section K.

Table 8: Wage Differentials with Finer Grids

Dependent Variables	Hourly Wage (OLS)				IV
	(1)	(2)	(3)	(4)	(5)
High-Performing	3.850***	2.704***	2.705***	2.731***	8.99***
	(0.0391)	(0.0453)	(0.0448)	(0.0448)	(0.9614)
Constant	47.24***	21.38	23.90	47.56***	41.85***
	(0.0701)	(22.75)	(22.51)	(0.0427)	(0.8755)
Time Controls:					
Day-Hour	Y	Y			
15Minute			Y		
Location Controls:					
Origin/Destination	Y				
Grid		Y	Y		
Grid-15Minute				Y	Y
Observations	4,182,318	3,160,528	3,160,528	3,160,528	3,160,528
R-squared	0.050	0.075	0.094	0.097	(omitted)

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The observation gap between Column (1) and Columns (2)-(5) arises from drivers who have not been active in the last hour and therefore lack grid information.

High-Performing Drivers Strategically Cancel Orders

Second, the literature shows that more experienced drivers learn how to strategically reject and cancel rides, hence earning more. To examine whether such a mechanism exists in our data, we regress the probability of a driver canceling an order on driver type and control for day-hour, origin, and destination fixed effects. Results in column (1) of Table 9 show that, if anything, high-performing drivers have a lower cancellation rate than low-performing drivers in our data. The robustness check results, controlling for finer location and time-fixed effects, remain consistent with these findings. It is very difficult for drivers to cancel an order on Platform X , which may help explain why Platform X drivers behave differently from Uber drivers described in Cook, Diamond, Hall, List and Oyer (2021). Because high-performing drivers have a lower probability of canceling an order, it is unlikely that the higher hourly wage of high-performing drivers is caused by drivers strategically rejecting and choosing rides in our case.

High-Performing Drivers Drive Faster

Third, some drivers may drive faster than others, hence completing more trips and earning a higher hourly wage. We examine whether high-performing drivers drive faster than low-performing drivers by regressing the average drive speed per hour on an indicator of being high-performing. We continue to control for day-hour, origin, and destination fixed effects. Column (2) of Table 9 shows the results. While we do find that high-performing drivers drive slightly faster (0.5%) than low-performing drivers, the 0.5% faster-driving speed is insufficient to explain the 8% wage differential we find in our main analysis. This 0.5% faster-driving speed only converts into an extra 0.24 CCY per hour,[18] thus explaining very little of the 3.8 CCY (or 8%) wage differential between high- and low-performing drivers.

High-Performing Drivers Know the Routes Better

Lastly, some may argue that high-performing drivers know the streets better; hence, high-performing drivers may use shortcuts or less congested routes to their benefit. As our dataset contains only the origin and destination of each ride, we do not observe the exact route chosen by the driver. However, based on our interviews with Platform X drivers and engineers, we find that drivers mostly follow the GPS-recommended route given by the Platform X app,

[18] The average driving speed for a low-performing driver is 24.63 km/h. Thus, by driving 0.5% faster, high-performing drivers drive 0.12 km more per hour. The average ride fare is about 2 CCY/km. Therefore, assuming that the extra 0.12 km is entirely used in carrying a rider without any time wasted, waiting for and picking up customers, then $0.12 * 2 = 0.24$ CCY. Therefore, this 0.5% faster-driving speed only converts into an extra 0.24 CCY per hour.

Table 9: Driver Cancellation and Driver Speed

Dependent Variables	Probability of Cancellation (by Driver)	Driving Speed
	(1)	(2)
High-performing	-0.0062***	0.1313***
	(0.0002)	(0.0194)
Constant	0.0365***	0.410***
	(0.0003)	(0.0006)
Mean of Low-performing	3.4%	24.63 (km/h)
High-performing compared to Low-performing	-18.2%	0.5%
Observations	4,815,026	4,168,889
R-squared	0.004	0.089

Notes: Standard errors are in parentheses. We control for day-hour fixed effects, origin district fixed effects, and destination fixed effects. *** p<0.01

as riders may file complaints to Platform X if drivers do not follow the suggested route. Therefore, drivers have less incentive to deviate from the recommended route.

To summarize, we examine four alternative explanations for the wage differential between high-performing and low-performing drivers: that high-performing drivers may strategically choose where to work, strategically select and cancel orders, drive faster, and have a better knowledge of routing. However, upon more in-depth analysis within our data, we rule out all four potential explanations as likely to explain the observed wage differential between high-performing and low-performing drivers.

5 Model

Given that the preferential algorithm prioritizes specific drivers based on their work schedule for order assignments, the labor supply decision is now subject to the rules specified by the preferential algorithm. To understand who benefits and who loses under such a preferential algorithm, we propose a dynamic equilibrium model of a ride-hailing market, similar to Frechette, Lizzeri and Salz (2019). In our model, each driver decides when and how long to work, depending on the wage rates and reservation values.

We model the decisions of market participants for one day. At each hour of the day, there is a demand curve for rides, $D_t(P_t)$. Given this demand curve, the platform makes two types of decisions. The platform first determines the price to charge riders, P_t. We allow for dynamic pricing and thus allow prices to vary across different times of the day. Second, the platform's algorithm allocates ride orders to each driver. The algorithm distinguishes between two types of drivers: high-performing and low-performing. High-performing drivers commit to working consecutively for at least 2 hours during incentivized hours between 10 AM–4 PM and 7 PM–6 AM the next day. Low-performing drivers make no work schedule commitments. A driver i first decides whether to be a high-performing or low-performing driver type $\tau \in \{H, L\}$. We assume that drivers choose their type (H or L) at the start of the day, and drivers cannot change their worker type throughout the day. Conditioning on the choice of being H-type or L-type, each driver chooses whether to work for each hour of the day. The problem is dynamic, because whenever a driver starts working or resumes working after a break, there is a fixed "warm-up" cost. If the driver chooses to be the high-performing type, the dynamic problem is under the constraint that working hours need to satisfy certain work schedules. Otherwise, the problem is unconstrained.

Our model prioritizes within-day dynamics over day-to-day dynamics to emphasize the major trade-off involved in drivers' standard decision-making process. According to our interviews with drivers, they tend to maintain a consistent working habit from day to day. This behavior may be attributed to the fact that initial introduction of ride-hailing in the focal market was back in 2014, leading to drivers establishing their daily patterns by the time of our study in 2018, whether as full-time or part-time drivers. Our data also validates this consistency in their hourly driving patterns. While it is technically feasible to incorporate day-to-day dynamics into our existing one-day model, doing so presents significant challenges due to data limitations and computational complexities. As a result, we leave this to future research. Investigating day-to-day dynamics could offer interesting insights into how drivers make choices among platforms and whether they opt to become ride-hailing drivers. As per our interviews with drivers, day-to-day dynamics are typically established within a short period. For individuals who have not yet settled into a consistent routine, choosing full-time ride-hailing work requires making arrangements with family members, such as finding suitable daycare for their children. Once drivers have settled into their day-to-day dynamics, they revert to the within-day dynamics as described in our study.

We use bold typeface to denote vectors containing values for each hour of the day. For example, $\boldsymbol{P}$ denotes all prices for all $t = 1, \cdots, 24$. The sequence of wage rates is $\boldsymbol{W^{\tau}}$, which is determined by the platform's pricing decisions $\boldsymbol{P}$ and the algorithm deciding which driver receives the orders.

5.1 Drivers' Dynamic Labor Supply

Drivers first choose either to be a high-performing or low-performing type. Low-performing drivers solve an unconstrained dynamic discrete choice problem of when to work. Per our discussion in Section 3, high-performing drivers are required to work consecutively for at least 2 hours during incentivized hours between 10 AM–4 PM and 7 PM–6 AM the next day. Besides fulfilling the required working hours, a high-performing driver makes an hourly choice of whether or not to work. If a driver chooses to be high-performing, the driver chooses which minimum requirement to satisfy in advance. For example, driver A may choose to be a high-performing driver by committing to work between 10 AM and 12 PM. Between 10 AM and 12 PM, driver A will be active on the app with probability 1, and at any other time of the day, driver A can freely choose whether to work or not. We assume that drivers choose their work type (H or L) at the start of the day, and drivers cannot change their type during the day. A low-performing driver B does not commit to any work schedule. *Ex post*, even if driver B ends up working long hours, including from 10 AM to 12 PM, driver B would still be considered a low-performing type.

Sixteen possible work schedules satisfy the high-performing requirement.[19] Work status is summarized by different work schedules, $\mathcal{L} \equiv \{0\}$ and $\mathcal{H} \equiv \{1, \cdots, 16\}$. The choice of work schedule is a simple logit model that motivates

$$N^j = N \cdot \frac{\exp(EV^j)}{\sum_{k=0}^{16} \exp(EV^k)},$$

where N is the total number of potential drivers, and EV^j represents the expected value of choosing work schedule j.[20] Therefore, the total number of high-performing drivers is $N^H = \sum_{k=1}^{16} N^k$, and the total number of low-performing drivers is $N^L = N^0$.

After deciding whether to be H-type or not, drivers then find the optimal solution to their dynamic discrete choice problem by choosing whether to work at each time t. Drivers observe the warm-up cost κ, sequence of hourly wages $\boldsymbol{W^\tau}$, and reservation values $\boldsymbol{O}$. Low-performing drivers, at each time t, compare the hourly wage plus the difference in expected future values to the value of their outside option. Then, the driver decides whether to work at time t. It is a dynamic problem, because if the driver chooses to work at time t and continues working at $t+1$, the driver would not need to pay an extra warm-up cost at $t+1$. Hence, the expected value for the future at time t is higher if the driver chooses to work

[19] For example, if a driver chooses to satisfy the high-performing requirement by working 10 AM–12 PM, then the driver is categorized as schedule 1. If a driver chooses to satisfy the high-performing requirement by working 11 AM–1 PM, then the driver is categorized as schedule 2, etc.

[20] We use the number of unique drivers in the 21 workdays as the number of potential drivers in our model.

than if the driver chooses not to work at time t. High-performing drivers have to work with probability 1 during committed hours. At any other time of day, high-performing drivers solve the same dynamic discrete choice problem by comparing the hourly wage plus the difference in expected future values to their outside option and decide whether to work at each time t.

Specifically, at the beginning of hour t, a driver receives a random draw from the wage distribution and another draw from the outside option:

$$\begin{aligned} U_{1t}^{\tau} &= \underbrace{W_t^{\tau}}_{\text{preferential wage rate}} + \sigma \cdot \epsilon_{1t}, \\ U_{0t}^{\tau} &= \underbrace{O_t^{\iota}}_{\text{outside option value}} + \sigma \cdot \epsilon_{0t}, \end{aligned} \tag{1}$$

where O_t^{ι} represents the reservation value from working on something else, and $\epsilon_{\cdot t}$ represents the error term that is Type-I extreme value distributed. Differences in reservation values among various groups of drivers may impact their labor supply decisions. To account for this, we consider the presence of unobserved heterogeneity in drivers' reservation values. Specifically, we have $O_t^{\iota} = O_t + \eta_{\iota,t}$, where O_t is the average reservation value per hour, and $\eta_{\iota,t}$ is driver-specific unobserved heterogeneity representing their preference for certain parts of the day. According to our survey of drivers, these preferred parts often closely align with the intervals on Platform X's fare schedule.[21] Therefore, we consider seven unobserved heterogeneity types that align with these intervals. For the benchmark driver group 0, the unobserved heterogeneity term η_{0t} is set to 0 for all time periods t. In contrast, driver group 1 has an unobserved heterogeneity term η_{1t} equal to η_1 during the time range from 7 AM to 10 AM and 0 for all other time periods. Similarly, driver group 2 shows an unobserved heterogeneity term η_{2t} equal to η_2 during the period from 10 AM to 4 PM.

There is a fixed warm-up cost $\kappa > 0$ to start working if the driver took the outside option in the previous hour. This is to rationalize that drivers often drive for consecutive hours. The value function for the low-performing driver at any time t that is not the first or the last period is derived as

$$V_t^L = \begin{cases} W_t^L + \sigma \cdot \epsilon_{1t} + \beta E V_{1t+1}^L & \text{if } a_t = 1 \text{ \& } a_{t-1} = 1, \\ W_t^L - \kappa + \sigma \cdot \epsilon_{1t} + \beta E V_{1t+1}^L & \text{if } a_t = 1 \text{ \& } a_{t-1} = 0, \\ O_t^{\iota} + \sigma \cdot \epsilon_{0t} + \beta E V_{0t+1}^L & \text{if } a_t = 0. \end{cases}$$

[21] Details of the fare schedules are explained in Section 2.1.

Here, W_t^L represents the wage rate for the low-performing driver at time t, κ is the warm-up cost, and σ is the scale parameter. The terms EV_{1t+1}^L and EV_{0t+1}^L denote the expected values if the driver chooses to work or not to work, respectively, at time t. The labor supply decision of the driver is denoted by a_t, where $a_t = 0$ indicates not working at time t. The value functions for all time periods of both low- and high-performing drivers can be found in Appendix B. We solve the dynamic discrete choice problems through backward induction. Individual driver choices, in turn, generate the aggregate labor supply for each hour by driver type:

$$N_t^H = \sum_{j=1}^{16} N^j \times \text{Pr(work in hour t|work schedule j)},$$
$$N_t^L = N^0 \times \text{Pr(work in hour t|work schedule 0)},$$

where the conditional choice probabilities $\Pr(\cdot|\cdot)$ are the solutions to the above-mentioned dynamic discrete choice problems. We denote the type-specific labor supply as

$$N_t^H = \mathcal{N}_t^H(\boldsymbol{W^H};\boldsymbol{\theta}) = \mathcal{N}_t^H(\boldsymbol{P},\boldsymbol{s};\boldsymbol{\theta}),$$
$$N_t^L = \mathcal{N}_t^L(\boldsymbol{W^L};\boldsymbol{\theta}) = \mathcal{N}_t^L(\boldsymbol{P},\boldsymbol{s};\boldsymbol{\theta}).$$

5.2 Demand for Rides and the Platform's Problem

Riders only demand driver-earning hours. The number of earning hours demanded is $D_t(P_t)$, where P_t is the hourly serving rate that the platform posts at hour t. For simplicity, we assume that demand for rides is downward-sloping and iso-elastic:

$$Q_t = D_t(P_t) = \delta_t P_t^{-\epsilon}, \tag{2}$$

where ϵ is the constant demand elasticity. The demand shifter δ_t includes daily weather indices, such as precipitation and temperature.

The platform takes demand shifter δ_t and demand elasticity ϵ as given and chooses prices and assignments to balance the demand and supply of rides to maximize platform profit. Let s_t be the fraction of orders assigned to high-performing drivers at time t, where $s_t \in [0,1]$. The platform's choice of $(\boldsymbol{P},\boldsymbol{s})$ maximizes its own payoff:

$$
\begin{aligned}
\max_{(\boldsymbol{P},\boldsymbol{s})} \quad & r\sum_t P_t D_t(P_t) \\
\text{s.t.} \quad & D_t(P_t)s_t \leq \lambda_t^H \mathcal{N}_t^H(\boldsymbol{P},\boldsymbol{s};\boldsymbol{\theta}) \\
& D_t(P_t)(1-s_t) \leq \lambda_t^L \mathcal{N}_t^L(\boldsymbol{P},\boldsymbol{s};\boldsymbol{\theta}).
\end{aligned} \tag{3}
$$

Here, r represents the platform's commission rate, while the drivers receive $1-r$ portion of the ride fare. $D_t(P_t)$ is the demand for rides measured in earning hours, and $\mathcal{N}_t^\tau$ represents the total number of working hours (active app hours) provided by the drivers. We have λ_t^τ as the technological constraint restricting the relationship between working hours and earning hours, where $\lambda_t^\tau \in [0,1]$. For example, $\lambda_t^\tau = 0.5$ means that for every 15 minutes driving with a rider, a typical driver spends another 15 minutes on pick up, payment, etc. If $\lambda_t^\tau = 1$, there is no time spent on pick up.[22] We have idle drivers waiting for trip requests when one of the two inequalities is unbounded. In our empirical analysis, we set the commission rate r equal to 20%.[23]

Given the choice of prices and assignments $(\boldsymbol{P},\boldsymbol{s})$, the platform effectively determines the sequence of wages $(\boldsymbol{W^H}, \boldsymbol{W^L})$. Each high-performing and low-performing type expects to receive a wage rate:

$$
\begin{aligned}
W_t^H &= (1-r)P_t D_t(P_t)s_t \frac{1}{N_t^H}, \\
W_t^L &= (1-r)P_t D_t(P_t)(1-s_t)\frac{1}{N_t^L},
\end{aligned} \tag{4}
$$

where $1-r$ is the revenue share that the driver receives; s_t represents how the algorithm favors high-performing drivers (the proportion of orders assigned to high-performing drivers).

6 Estimation

6.1 Demand Estimation

We first estimate rider demand for service time for each hour h. We consider each hour a different market and aggregate our data to the day-hour level. We obtain the logarithm of total earning time (Q_t) and the logarithm of average hourly ride fare (P_t). Demand

[22] We obtain the value of the technological constraint from the data. We compute the driving time as a fraction of driver work time in each day-hour for high-performing and low-performing drivers. Then, we calculate the maximum as the technological restriction.

[23] According to Platform X's IPO document, the national average commission rate is 20.9%. In our survey, most drivers suggest that the commission rate is about 20%. Therefore, we use $r = 0.2$ in our empirical analysis.

parameters are estimated through:

$$\log Q_t = \log \delta_h - \epsilon \log P_t + e_h. \tag{5}$$

Our demand estimation suffers from classic supply-demand endogeneity. The platform may set a higher price when there is a higher demand shock in the market. Therefore, our OLS estimates may be biased. Similar to Kalouptsidi (2014), we use the number of cars in competing ride-hailing companies on the given day as our supply-side instrumental variable. Suppose the hourly demand shock e_h is instantaneous with an expected value of zero *ex ante*. In that case, the number of cars in competing ride-hailing companies is not correlated with hour-level demand shocks. On the other hand, the number of cars competitors operate is negatively correlated with the ride fare that the platform can charge. Therefore, the number of cars in competing ride-hailing companies is a valid instrument.

Table 10: Demand Estimation

Dependent Variables	ln(Service Hours)			
	(1) OLS	(2) OLS	(3) OLS	(4) IV
ln(Hourly Wage)	-5.151***	-5.158***	-0.767***	-1.186**
	(0.0743)	(0.0737)	(0.152)	(0.553)
Rain		-0.0020	-0.0005	-0.0006
		(0.002)	(0.0007)	(0.0007)
Temperature		0.0127***	0.0094***	0.0098***
		(0.0033)	(0.0011)	(0.0012)
Constant	32.12***	32.06***	10.62***	12.69***
	(0.350)	(0.348)	(0.752)	(2.736)
Hour FE			Y	Y
Day of Week FE			Y	Y
Observations	744	744	744	744
R-squared	0.866	0.869	0.988	0.988

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10 reports demand estimates for the city of study. Column (1) reports the estimates without fixed effects. Column (2) reports estimates with the weather as a demand shifter. Column (3) further includes day and hour fixed effects. Column (4) reports our IV estimates. After controlling for hourly fixed effects and day-of-the-week fixed effects, column (3) reports a demand elasticity of -0.767. The estimated demand elasticity is much smaller with fixed effects than the estimates in the naïve OLS regression. Our IV estimates in column (4) are similar to those with fixed effects in column (3). The IV estimates show that when the hourly ride fare increases by 1%, the total demand for service time decreases by 1.2%. We use the IV estimate as the value of demand elasticity in our counterfactual analysis. Our estimated demand elasticity of -1.186 is comparable to the values estimated in the literature. Frechette, Lizzeri and Salz (2019) estimates an elasticity of -1.225 for New York City's taxi market. Cohen, Hahn, Hall, Levitt and Metcalfe (2016) relies on the surge pricing algorithm and estimates a smaller price elasticity for UberX (between -0.4 and -0.6).

6.2 Estimation of Structural Parameters

Our model with unobserved heterogeneity is point-identified using conditional choice probabilities in drivers' dynamic labor supply. Appendix C contains the details of our identification arguments.

Next, we estimate the structural parameters: $\boldsymbol{\theta} \equiv (\{O_t\}, \kappa, \sigma)$. $\{O_t\}$ is the reservation value at each time t, which includes the average reservation value R_t and the unobserved heterogeneity $\{\eta_{s,t}\}$. κ is the warm-up cost of starting to work, and σ is the normalization term of EVT1 errors (the scale parameter). We follow Arcidiacono and Miller (2011) in estimating the unobserved heterogeneity, and we explain the details of our estimation procedure in Appendix C.2.

Table 11 shows the estimation results. The first row shows the estimated population density of each driver group. We can see that three main driver groups dominate: group 3 with probability 0.42, group 2 with probability 0.18, and group 4 with probability 0.18. The second row of Table 11 shows the probability of being high-performing for each driver group. Driver group 2 is high-performing with probability 96.5%, and group 4 is high-performing with probability 93.4%. Meanwhile, driver groups 2 and 4 have the lowest average reservation values.

Table 11: Estimation Results of Unobserved Heterogeneity

	Group 0	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Population density of each group	0.07	0.06	0.18	0.42	0.18	0.04	0.05
Probability of H-Type	76.7%	78.7%	96.5%	49.6%	93.4%	82.8%	81.0%
Average Reservation Value	46.2	45.6	36.5	50.9	40.6	45.1	44.8

Figure 3 shows the estimated reservation values with unobserved driver heterogeneity. The average estimated reservation value is 49 CCY. The black line shows the estimated reservation values for the benchmark case. The reservation value is lowest during morning hours, around 25 CCY, and highest at late night, around 68 CCY. For context, the minimum hourly wage in the city of the study was 18.5 CCY in 2018. From the estimated results, we can see that drivers have higher reservation values during incentivized hours between 10 AM—2 PM and 7 PM—5 AM. It helps explain why the ride-hailing platform wants to implement algorithmic preferential wage-setting to incentivize drivers to work more during incentivized hours. In terms of driver heterogeneity, driver groups 2 and 4 exhibit low reservation values during mid-day and early-night periods, respectively. The estimated warm-up cost is 124 CCY, around 2.5 times the average hourly reservation value. The high warm-up cost helps explain why drivers usually choose to drive consecutive hours.

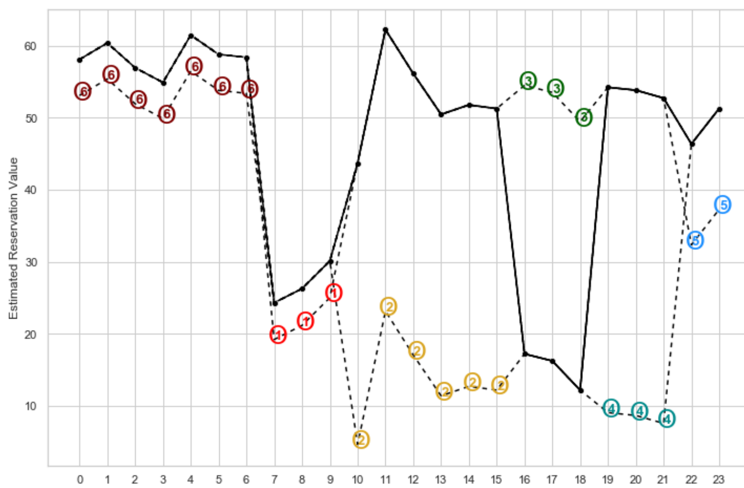


Figure 3: Estimated Reservation Values with Unobserved Driver Heterogeneity

Table 11 shows that three main driver groups dominate: the benchmark drivers (group 3), drivers with low mid-day reservation values (group 2), and those with low early-night reservation values (group 4). To better understand the estimated driver groups, we associate the observed driver characteristics with the respective driver groups. Because driver group 2 has a low mid-day reservation value and a high probability of being high-performing, observed high-performing drivers who choose to work mid-day are more likely to be in driver group 2. Similarly, observed high-performing drivers who work early night are more likely to be in driver group 4. Based on this definition, we divide observed high-performing drivers into several groups according to their working hours. The *Day* group refers to drivers who work at least 2 consecutive hours in the daytime for at least 8 of 21 workdays.[24] The *Night* group refers to drivers working at least 2 consecutive hours at night for at least 8 of 21 workdays. Drivers who satisfy both criteria belong to the *Day&Night* group. The three groups (*Day*, *Night*, *Day&Night*) are mutually exclusive. The rest of the high-performing

[24]This is consistent with our definition of high-performing drivers, who we require to satisfy the condition in at least 8 of the 21 workdays.

drivers are grouped into the *Rest* group.

Table 12 compares the driver characteristics of different driver groups in the data, with several interesting findings. First, the *Day* group has a higher proportion of female drivers (3.5%) than the *Night* group (1.2%). Second, the average age in the *Day* group (38.3) is higher than that of the *Night* group (36.5). Third, non-locals are more likely to be high-performing drivers. For instance, 76% of the drivers in the *Day&Night* group are non-local drivers, compared to 62% non-local drivers in the *Night* or *Day* groups, and 53% non-local drivers for the low-performing drivers. Therefore, the results suggest that driver groups 2 and 4 are more likely to consist of older, non-local, and female drivers. On the other hand, driver group 3 is more likely to include younger, local, and male drivers. By associating observed driver demographics with estimated driver groups through unobserved heterogeneity, in the counterfactual analysis we can better understand which individuals may benefit or suffer from the implementation of a preferential algorithm.

Table 12: Observed Driver Characteristics

Type	Low-Performing	High-Performing			
Group		Night	Day	Day&Night	Rest
Female	3.5%	1.2%	3.5%	1.7%	1.6%
Age	37.4	36.5	38.3	36.8	36.4
Non-local	53%	62%	63%	76%	62%
# of Drivers	16,392	3,073	6,659	11,939	2,041

Last, we validate our model by checking the model's goodness of fit. Specifically, we examine whether the simulated values fit the observed CCPs well. Figure D.1 shows the model's goodness of fit. Overall, the simulated values fit the observed CCPs well.

7 Counterfactual Analysis

We conduct two main counterfactual experiments. First, we show the welfare effects of eliminating the preferential algorithm in the short and long term. In the short term, ride fares are held fixed. The platform will re-optimize its pricing strategy and change ride fares in the long term. Second, we investigate what factors determine the effectiveness of the preferential algorithm. Primarily focusing on the demand parameter ϵ (demand elasticity) and the warm-up cost parameter κ, we examine how the value of these key structural parameters affect the welfare implications of a preferential algorithm.

7.1 Elimination of Preferential Algorithm ("Fair" Pay)

In the first counterfactual analysis, we study changes in welfare if the preferential algorithm based on work schedules is eliminated. In this case, orders would be randomly assigned to nearby active workers. Effectively, the hourly wage each driver earns will become

$$\widetilde{W}_t = \frac{\eta P_t D_t(P_t)}{N_t}.$$

Given the new sequence of hourly wages $\{\widetilde{W}_t\}$, drivers solve the unconstrained dynamic discrete choice problem for each hour t:

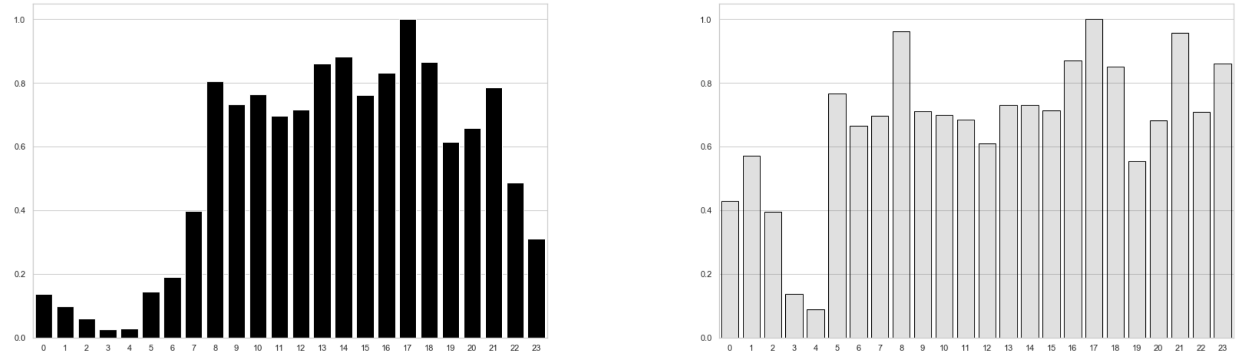
$$\begin{aligned} U_{1t} &= \underbrace{\widetilde{W}_t}_{\substack{\text{non-preferential} \\ \text{wage rate}}} + \sigma \cdot \epsilon_{1t}, \\ U_{0t} &= \underbrace{O_t}_{\text{outside option value}} + \sigma \cdot \epsilon_{0t}, \end{aligned}$$

where we have replaced the preferential wage rates W_t^H and W_t^L by the "fair" rate $\widetilde{W}_t$. In the short term, ride fares without the preferential algorithm are held the same as ride fares with the preferential algorithm.

First, we show how the platform leverages cross-time elasticity using the preferential algorithm. When ride fares are fixed in the short term, eliminating the preferential algorithm will decrease labor supply, resulting in labor shortages for most hours. Panel (a) of Figure 4 shows the level of labor shortage.[25] We can see a severe labor shortage during mid-day and in the late afternoon when we eliminate the preferential algorithm in the short term. Panel (b) shows the wage differential between high-performing and low-performing drivers when the preferential algorithm is present. A high wage differential in a particular hour means a high incentive wage for that hour. The results show that the relation between wage differentials and labor shortages is not one-to-one. For example, there is a severe labor shortage at 1 PM and 2 PM; however, the platform does not directly provide high incentive wages at 1 PM and 2 PM specifically. Instead, the platform provides high incentive wages from 5 AM to 8 AM. Panel (a) shows that the labor shortage is very mild from 5 AM to 7 AM in the early morning. Therefore, the platform does not necessarily provide direct high incentive wages to mitigate labor shortages in a given hour, but instead smooths out the payment of high incentive wages by leveraging cross-time elasticity differences.

To further illustrate the idea of cross-time elasticity, we eliminate the wage differential

[25]To better illustrate the results, we normalize the maximum labor shortage and the maximum wage differential to 1 in Figure 4.



(a) Labor Shortage

(b) Wage Differential (W_t^H - W_t^L)

Figure 4: Illustration of Leveraging Cross-time Elasticity

between high-performing and low-performing drivers in only one hour (the treatment hour) and study the implied elasticity of labor supply. Precisely, we calculate the elasticity as

$$\mathcal{E}_t^\tau(h) = \frac{\left(N_t^\tau(\widetilde{\boldsymbol{W}}^H, \widetilde{\boldsymbol{W}}^L) - N_t^\tau(\boldsymbol{W}^H, \boldsymbol{W}^L)\right) / N_t^\tau(\boldsymbol{W}^H, \boldsymbol{W}^L)}{(\widetilde{W}_h^\tau - W_h^\tau)/W_h^\tau},$$

where h is the chosen hour where we eliminate the wage differential between high-performing and low-performing drivers. Figure 5 shows the absolute value of the elasticity of labor supply corresponding to the elimination of the wage differential at 12 PM. The blue line represents the low-performing drivers, while the red line represents the high-performing drivers. Low-performing drivers are much more responsive to the elimination of the wage differential than high-performing drivers. On the one hand, high-performing drivers' labor supply is inelastic in all hours (less than 0.7). On the other hand, low-performing drivers' labor supply elasticities are higher than 0.9 in all hours and even higher than 1 in the hours near the treated hour. The absolute elasticity value generally decreases for hours further away from the treatment hour. It is because there is a high warm-up cost of starting to work, so adjacent hours of the treatment hour will be affected more. However, the absolute elasticity value does not monotonically decrease with respect to the distance to the treatment hour because of the variation in reservation values across the different hours of the day. Given that multiple-hour labor supply responds to the wage differential at one particular hour, the platform can strategically choose when to provide high incentive wages. In Appendix I, we replicate this exercise by changing the treatment hour from 7 AM to 6 PM.

Next, we show the welfare effects of eliminating the preferential algorithm. We study the welfare effects in both the short run and the long run. In the long run, the platform will

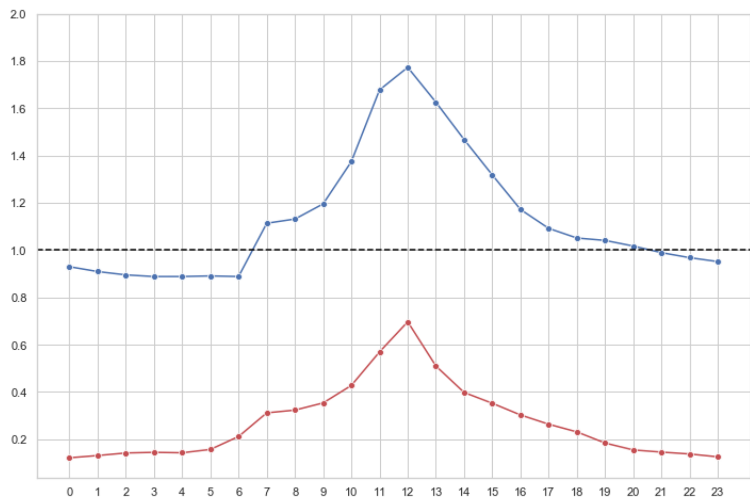


Figure 5: Elasticity of Labor Supply When Eliminating Wage Differential at 12 PM

re-optimize the hourly ride fares $\boldsymbol{P}$ to maximize its payoff:[26]

$$\begin{aligned} \max_{\vec{P}} \quad & (1-\eta)\sum_t P_t D_t(P_t) \\ \text{s.t.} \quad & D_t(P_t) \le \widetilde{\lambda}_t \mathcal{N}_t(\boldsymbol{W_t};\boldsymbol{\theta}) \end{aligned} \tag{6}$$

Using the estimated parameters, we solve for the new equilibrium outcome if the platform can no longer implement algorithmic preferential wage-setting based on the work schedule. Then, we calculate the changes in platform revenue, consumer surplus, and driver surplus by comparing the outcome without the preferential algorithm to the outcome with the preferential algorithm. We calculate consumer welfare as $\sum_t \int_{P_t}^{\infty} \delta_t x^{-\epsilon} dx$ and the driver surplus of each schedule j as

$$EV_0^j = \sigma\left[\ln\left(\exp((\widetilde{W}_1 - \kappa + \beta EV_{12})/\sigma) + \exp((O_1 + \beta EV_{02})/\sigma)\right) + \gamma\right],$$

where EV_0^j represents the expected value choosing each work schedule type j.[27] Table 13 shows the results. In the short term, eliminating the preferential algorithm will result in a massive loss for both the platform and the rider because of a driver shortage on the one hand. On the other hand, drivers enjoy more flexibility in choosing a work schedule under "fair"

[26]Note that the two feasibility constraints in equation 3 become one because all drivers have the same likelihood of receiving a task, and $\widetilde{\lambda}_t$ is the technology restriction without algorithmic preferential wage-setting. Under "fair" pay, there is only one group, so $s = 1$.

[27]Note that consumer surplus $\sum_t \int_{P_t}^{\infty} \delta_t x^{-\epsilon} dx = \sum_t \frac{\delta_t}{\epsilon - 1}(P_t)^{1-\epsilon} = \frac{1}{(\epsilon-1)(1-\eta)} \times$ platform revenue. In the short term, the total number of riders served equals to $\min\{D_t(P_t), \widetilde{\lambda}_t \mathcal{N}_t(\boldsymbol{W_t};\boldsymbol{\theta})\}$.

pay. Hence, there will be a 0.14% increase in driver surplus. High-performing drivers suffer a loss of 0.63% because there is no longer a bonus for being high-performing. Low-performing drivers see an increase in hourly wage, hence a 0.63% increase in surplus. In aggregate, the total surplus will decrease by 7.16% if we eliminate the preferential algorithm.

Table 13: Changes in Welfare

Changes in	short term	long term
Platform revenue	-12.16%	-1.42%
Consumer surplus	-12.16%	-1.42%
Driver surplus	0.14%	0.49%
Total surplus	-7.16%	-0.64%
Decomposition of Per-Driver Surplus		
High-performing driver (non-switcher)	-0.63%	-0.16%
Low-performing driver (non-switcher)	0.69%	0.99%
Switcher (from H-type to L-type)	3.51%	3.81%
Change in Probability of being H-type	-11.48%	-9.98%

Notes: We calculate changes in welfare by measuring the results without a preferential algorithm minus the results with a preferential algorithm. In the short term, ride fares without a preferential algorithm are held the same as ride fares with a preferential algorithm. In the long term, the platform re-optimizes its pricing strategy without a preferential algorithm.

In the long term, the platform will re-optimize its pricing strategy. The platform will increase ride fares to reduce the driver shortage that we see in the short term when we eliminate the preferential algorithm. As a result, the loss of platform and riders will be smaller in the long term compared to the short term, resulting in a total of 1.42% decrease in surplus. Driver surplus will increase further, because drivers benefit in the long term from the increased ride fare. Total driver surplus will increase by 0.49% if we eliminate the preferential algorithm. In the long term, low-performing drivers have a 1% increase in surplus because they benefit from more flexibility in working and a higher ride fare. Regarding the extensive margin, the probability of being high-performing decreases by 11.48 percentage points in the short term and decreases by 9.98 percentage points in the long term. After we eliminate the preferential algorithm, the probability of being high-performing drivers slightly increases in the long term compared to the short term. The total surplus will decrease by 0.64% if we eliminate the preferential algorithm.

Lastly, we look at how different groups of drivers are affected if we eliminate the preferential algorithm. We characterize driver groups by unobserved heterogeneity estimated in Section ??. Table 14 shows the results. First, we can see both winners and losers from eliminating the preferential algorithm. Driver groups 2 and 4 experience a decrease in their surplus by 0.36% and 0.22% respectively in the short term, while all other driver groups experience an increase in their surplus from the elimination of the preferential algorithm. The welfare loss of driver groups 2 and 4 is because they are more likely to be high-performing, and high-performing drivers will no longer earn extra hourly wages without the preferential algorithm. Previous results show that drivers in groups 2 and 4 are high-performing with probability 96.5% and 93.4%, respectively. Previous results also show that among high-performing drivers, female drivers and older drivers are more likely to fall into groups 2 and 4. Therefore, the counterfactual results indicate that women and older drivers who choose to be high-performing are more likely to suffer from eliminating the preferential algorithm. The general effect for female drivers is ambiguous, because women are also more likely to be low-performing with a larger welfare gain from the elimination of the preferential algorithm. Non-locals are more likely to have a welfare loss if we eliminate the preferential algorithm because they are more likely to be high-performing. All other driver groups (younger, local, male) will benefit from the elimination of the preferential algorithm.

Table 14: Change in Driver Surplus by Groups of Drivers

Changes in Driver Surplus	Driver Group						
	Group 0	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Panel I: Short term							
Total	0.08%	0.05%	-0.36%	0.20%	-0.22%	0.00%	0.07%
H-Schedule	-0.41%	-0.43%	-0.50%	-0.14%	-0.44%	-0.38%	-0.42%
L-Schedule	0.35%	0.38%	0.86%	0.12%	0.57%	0.37%	0.36%
Panel II: Long term							
Total	0.29%	0.28%	-0.02%	0.22%	0.08%	0.23%	0.29%
H-Schedule	-0.14%	-0.15%	-0.17%	-0.04%	-0.13%	-0.12%	-0.14%
L-Schedule	0.54%	0.58%	1.19%	0.16%	0.86%	0.57%	0.56%

Notes: We calculate changes in welfare by results without a preferential algorithm minus results with the preferential algorithm. We characterize driver groups by unobserved heterogeneity. In the short term, ride fares without a preferential algorithm are held the same as ride fares with a preferential algorithm. In the long term, the platform re-optimizes its pricing strategy without a preferential algorithm.

In summary, the platform benefits from implementing a preferential algorithm by leveraging the cross-time elasticity difference in labor supply. In the short term, eliminating the preferential algorithm results in a significant welfare loss for the platform and riders due to driver shortages. Drivers experience an increase in surplus because of more flexibility in choosing their work schedule. The platform will re-optimize pricing and increase ride fares in the long term. As a result, the driver shortage will be mitigated, and welfare loss will be smaller for the platform and riders. Drivers will have an even greater increase in welfare because of increased ride fares. Among different groups of drivers, male, young, and local drivers are more likely to benefit from the elimination of the preferential algorithm. Older drivers are likely to experience a welfare loss. The net effect for female drivers is ambiguous, with a welfare loss for high-performing female drivers and a welfare gain for low-performing female drivers.

7.2 Factors Determining Preferential Algorithm Effectiveness

To further investigate what factors determine the effectiveness of the preferential algorithm, we conduct counterfactuals by alternating key structural parameters. Motivated by our two-period model in Appendix **??**, we focus on the demand elasticity ϵ and warm-up cost κ. Table 15 shows the results when we alter the value of demand elasticity. When demand is more elastic, the platform benefits more from utilizing the cross-time difference in elasticity by implementing the preferential algorithm. Therefore, in column (1) of Table 15, we see a larger increase in platform revenue from 1.44% to 2.89% if the platform implements the preferential algorithm. On the other hand, drivers suffer less from the preferential algorithm if demand elasticity increases. Total driver surplus will decrease by 0.32% when demand is more elastic, compared to a decrease of 0.49% when demand is less elastic. The intuition is that when demand is very elastic, the platform is less willing to incentivize labor supply by increasing ride fares. Otherwise, the platform will see a large decrease in rider demand. Therefore, drivers will experience a smaller increase in wage rate when eliminating the preferential algorithm. Equivalently, this means that drivers will experience a smaller decrease in wage rate, and hence driver surplus, when the platform implements the preferential algorithm. Column (4) of Table 15 confirms this intuition by showing that the average decrease in wage is smaller (5.03% versus 7.26%) when demand is more elastic. As a result, the loss of low-performing drivers decreases from 0.98% to 0.17%.

Next, we examine the effect of the warm-up cost κ. Table 16 shows the results when we vary the value of the warm-up cost κ. When the warm-up cost is higher, the platform must pay higher wages to incentivize drivers to work. Hence, avoiding paying such high incentive wages by implementing the preferential algorithm is more profitable for the platform. On the other hand, saving these high incentive wages reduces the ride fare, and hence more riders can be served. Serving more riders also generates more hourly revenues for the drivers. As

Table 15: Varying the Value of Demand Elasticity ϵ

	Changes in (With - Without)			
Demand Elasticity	Platform Revenue/ Consumer Surplus	Driver Surplus	Driver Surplus (Low-performing)	Average Wage
Benchmark	1.44%	-0.49%	-0.98%	-7.26%
$\epsilon \times 1.1$	2.13%	-0.47%	-0.52%	-6.55%
$\epsilon \times 1.2$	2.60%	-0.40%	-0.29%	-5.78%
$\epsilon \times 1.3$	2.89%	-0.32%	-0.17%	-5.03%

a result, the loss in driver surplus from the preferential algorithm will be smaller when the warm-up cost is larger. Column (4) of Table 15 confirms the intuition by showing that the change in the number of served riders is greater (9.76% versus 9.55%) when the warm-up cost is larger.[28]

Table 16: Varying the Value of Warm-up Cost κ

	Changes in (With - Without)			
Warm-up Cost	Platform Revenue/ Consumer Surplus	Driver Surplus	Driver Surplus (Low-performing)	Consumers Served
Benchmark	1.44%	-0.49%	-0.98%	9.55%
$\kappa \times 1.1$	1.45%	-0.49%	-0.93%	9.64%
$\kappa \times 1.2$	1.46%	-0.49%	-0.86%	9.71%
$\kappa \times 1.3$	1.47%	-0.48%	-0.79%	9.76%

To summarize, the platform benefits more from implementing a preferential algorithm when the demand is more elastic or when the warm-up cost is greater. Meanwhile, the loss of driver surplus with a preferential algorithm is also smaller when the demand is more elastic or when the warm-up cost is greater.

[28] In the second case, when we alter the value of the warm-up cost κ, showing the change in average wage will not directly reveal how driver surplus changes, because driver utility is affected by both the warm-up cost and average wage. Instead, when demand elasticity is fixed in the second case, the surplus of low-performing drivers will monotonically increase with respect to the number of riders served. Similarly, in the first case, when we alter the value of demand elasticity η, showing the change in the number of riders served will not directly reveal how driver surplus changes, because the number of riders served is determined by the labor supply decision and demand elasticity. In the first case, when the warm-up cost is fixed, the surplus of low-performing drivers will monotonically increase with respect to the average wage rate. This is why we report different variables in the last column of Tables 15 and 16.

8 Conclusion

The rapid acceleration of algorithmic technologies has changed the relationship between workers and employers, and there is an urgent need to better understand the emerging challenges posed by algorithmic technologies. Our paper aims to provide the first empirical study of algorithmic wage-setting and its impact on worker behavior and welfare. Using rich transaction data from a leading ride-hailing company in Asia, we first document significant wage differentials due to work schedules between high-performing drivers who work long and consecutive hours and low-performing drivers. We show that three main factors drive the wage differential: high-performing drivers are given more ride requests per hour, wait fewer minutes for each request, and receive more requests from riders with lower cancellation rates. Next, we exclude alternative explanations of the wage differentials, such as drivers strategically choosing where to work, strategically selecting and canceling orders, driving faster, and having better knowledge of routes. The large wage differential we identify is mainly due to algorithmic wage-setting, which penalizes low-performing drivers. Our arguments highlight one important channel the literature has overlooked: the platform balances demand and supply through the *cross-time* elasticity of substitution in labor supply. We then propose a dynamic equilibrium model of a ride-hailing market to quantify the welfare effects of such a preferential algorithm. Results show that platform revenues will decrease by 12.16%, and the total surplus will decrease by 7.16% in the short term if we eliminate the preferential algorithm. The probability of drivers being high-performing will decrease by 11.48% without a preferential algorithm. For the switchers, driver surplus will increase by 3.51%. In the long run, raising rider fares re-balances demand and supply, resulting in minimal welfare loss. Moreover, an additional 10% of drivers would switch to flexible schedules. Among drivers, young, male, and local drivers benefit more from the elimination of the preferential algorithm. Lastly, we show comparative statistics of how demand elasticity or warm-up cost affects gains/losses from preferential algorithms. Our simulations show preferential algorithms benefit the platform more and hurt drivers less when rider demand is more elastic or when the warm-up cost is higher.

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A Preferential Algorithm and Surge-Pricing

The platform benefits from both surge-pricing and a preferential algorithm, although their mechanisms differ. To illustrate the contrasting ways surge-pricing and the preferential algorithm operate and to showcase their potential complimentarity, we use our theoretical model to solve equilibrium outcomes in the following four scenarios:

1. Without surge-pricing and preferential algorithm
2. With only surge-pricing
3. With only the preferential algorithm
4. With both surge-pricing and the preferential algorithm

As discussed in section 2, we consider a scenario with two time periods, denoted as t_1 and t_2. For both periods, the demand is assumed to be $P_t^d = 10 - q$. At time period t_1, drivers have a reservation value of 0. At time period t_2, drivers have positive and heterogeneous reservation values, and the supply curve is defined as $P_{t_2}^s = q$.

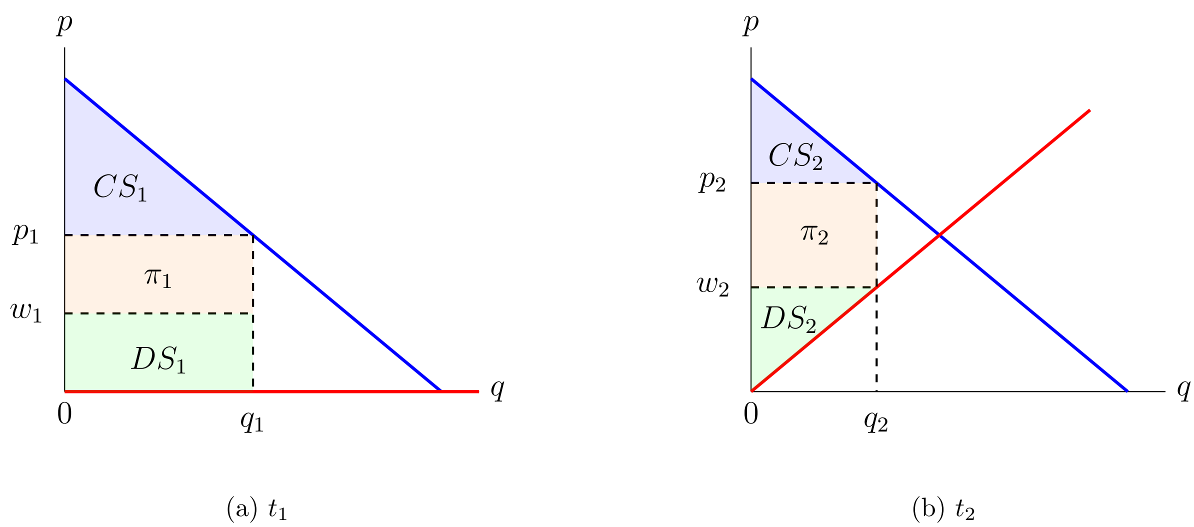
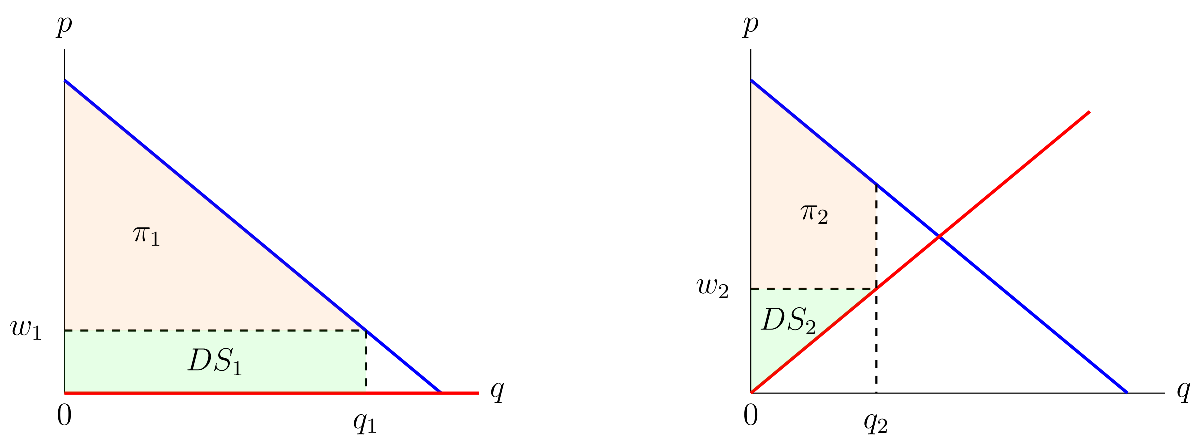


Figure A.1: Case 1, Without surge-pricing and preferential algorithm

In the baseline case, where neither surge-pricing nor a preferential algorithm is employed, the platform sets a price p_t for time period t, and drivers earn $w_t = (1 - \eta) * p_t$, where η represents the fractional commission fee. The platform's earnings in this case are calculated as $\eta * p_t * q_t$. For this numerical example, we assume $\eta = 0.5$. Figure A.1 shows the results for case 1. In both periods, the platform chooses the optimal ride fare p_t to maximize its profit. For the numerical example, the platform sets ride fares at $p_1^* = 5$ and $p_2^* = 6.67$, leading to wage rates of $w_1^* = 2.5$ and $w_2^* = 3.33$ for the drivers. The blue area in Figure A.1 represents the consumer surplus, the orange area represents the platform's profit, and the green area shows the drivers' surplus.

Figure A.2 shows the results for case 2, in which only surge-pricing is implemented. With surge-pricing, the platform captures the entire consumer surplus while offering a constant wage rate to the drivers in each period.[29] Consequently, the platform optimizes the wage rate to pay the drivers in this scenario. In the given numerical example, the optimal wage rate is set at $w_1^* = w_{min} = 2$,[30] and $w_2 = 3.33$. The implementation of surge-pricing results in a complete elimination of consumer surplus in both periods.



(a) t_1 (b) t_2

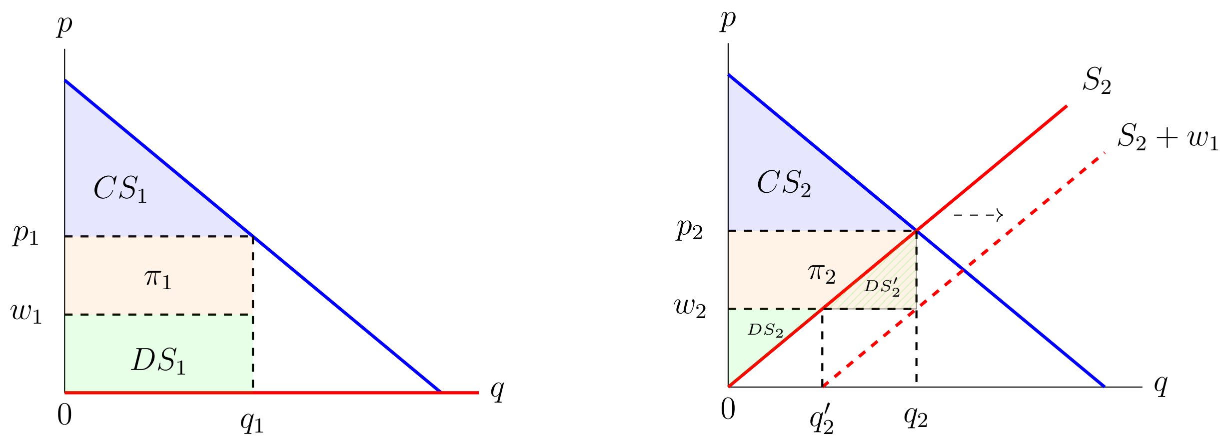
Figure A.2: Case 2, With only surge-pricing

Figure A.3 shows the results for case 3, in which only preferential algorithm is implemented. With a preferential algorithm, the platform communicates to drivers that if they work during time period t_2, they will be given priority and receive an order during time period t_1. Hence, the platform can motivate drivers to work during time period t_2 without offering extra incentive wages. As a result, the labor supply curve is shifted outwards at t_2, as illustrated by the dashed red line. In this scenario, the optimal prices are determined as $p_1^* = 5$ and $p_2^* = 5$, leading to $w_1^* = 2.5$ and $w_2^* = 2.5$, with the number of orders served being

[29] Alternatively, we can use the same wage scheme utilized in case 1, where drivers receive a constant fraction of the ride fare as their payment. This would lead to higher surplus for the drivers. However, to highlight the key tradeoff and to simplify the model here, we opt for a constant wage rate in this context.

[30] The platform is unable to further decrease wage rate at t_1 because of minimum wage requirement as explained in 2. Otherwise, the platform will charge $w_1^* = 0$ at t_1, resulting in no driver surplus during that period. Consequently, the implementation of the preferential algorithm on top of surge-pricing would no longer be feasible. To enable a meaningful comparison between case 2 and case 4, it is necessary to ensure a positive drivers' surplus at t_1 in this particular scenario.

$q_1^* = 5$ and $q_2^* = 5$. However, with a wage rate of $w_2^* = 2.5$, some drivers are actually earning a negative surplus at t_2. For drivers falling within the range of q_2' to q_2, the wage at t_2 is insufficient to cover their reservation values. Despite this, they are willing to work during this time period because they anticipate earning a positive surplus at t_1 with prioritized order assignment. The platform's profit at t_2 is represented by the orange rectangle π_2 in panel (b) of Figure A.3, which is calculated as $(p_2 - w_2) * q_2$. The driver surplus is equivalent to the green area $DS_2 - DS_2'$. The preferential algorithm serves to assist the platform in extracting additional driver surplus.

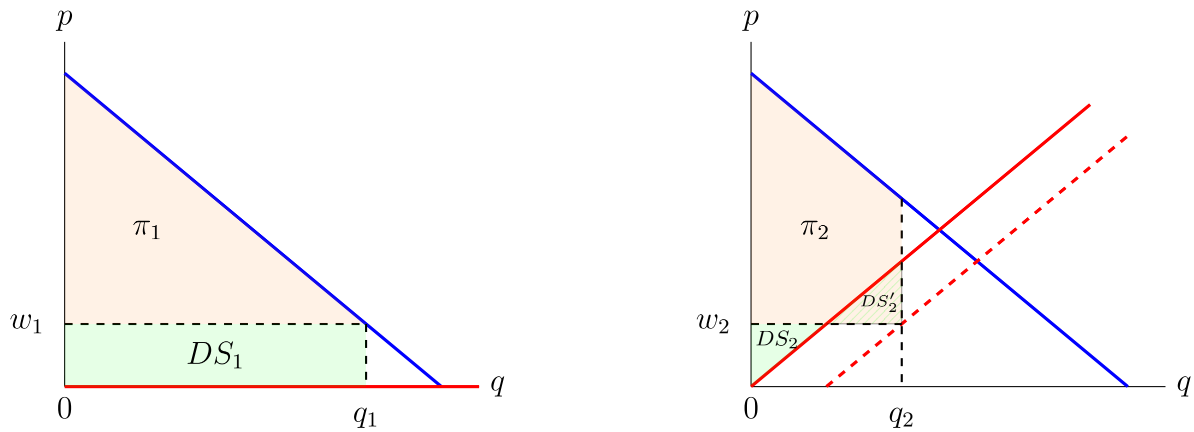


(a) t_1 (b) t_2

Figure A.3: Case 3, With only preferential algorithm

Figure A.4 shows the results for case 4, in which both surge-pricing and preferential algorithm are implemented. Firstly, similar to case 2, surge-pricing allows the platform to capture the entire consumer surplus. Additionally, in case 4, the platform further leverages the preferential algorithm to incentivize drivers to work more. In Figure A.4, the platform's profit is denoted as π_1 and π_2 respectively, while driver surplus is represented by DS_1 during time period t_1 and $DS_2 - DS_2'$ during time period t_2.

We proceed to compare the equilibrium outcomes in each scenario. Table A.1 provides a summary of the equilibrium profit of the platform, the ride fare, the wage rate, and the quantity served for each scenario. On the other hand, Table A.2 shows the consumer surplus, drivers surplus, and total surplus for the respective scenarios. We refer to the scenario where neither the preferential algorithm nor surge-pricing is implemented as the benchmark case (case 1). When comparing the results of case 2 with the benchmark case, we can see that by implementing surge-pricing, the platform serves more consumers during t_1. While drivers experience a lower wage rate at t_1, the total drivers' surplus increases from 12.5 to 16 due to



(a) t_1 (b) t_2

Figure A.4: Case 4, With both surge-pricing and preferential algorithm

the higher number of orders served. Consequently, with the implementation of surge-pricing, although the entire consumer surplus is captured by the platform, drivers also benefit from a higher driver surplus.

Table A.1: Equilibrium Outcomes

	Platform's profit		Price		Wage rate		Quantity	
	t_1	t_2	t_1	t_2	t_1	t_2	t_1	t_2
Case 1: No algorithm, no surge	12.50	11.11	5.00	6.67	2.50	3.33	5.00	3.33
Case 2: Only surge-pricing	32.00	16.67	/	/	2.00	3.33	8.00	3.33
Case 3: Only algorithm	12.50	12.50	5.00	5.00	2.50	2.50	5.00	5.00
Case 4: Both surge and algorithm	32.00	24.00	/	/	2.00	2.00	8.00	4.00

Table A.2: Comparing Surplus

	Driver Surplus		Consumer Surplus		Total Surplus
	t_1	t_2	t_1	t_2	$t_1 + t_2$
Case 1: No algorithm, no surge	12.50	5.56	12.50	5.56	59.72
Case 2: Only surge-pricing	16.00	5.56	0.00	0.00	70.22
Case 3: Only algorithm	12.50	0.00	12.50	12.50	62.50
Case 4: Both surge and algorithm	16.00	0.00	0.00	0.00	72.00

When comparing case 3, where only the preferential algorithm is implemented, with the benchmark case, we can see that the platform now charges lower ride fares and pays lower wage rates during t_2. Consequently, the driver surplus is reduced with the introduction of the preferential algorithm. However, on the other hand, consumers also benefit from the lower ride fares during t_2, resulting in an increase in consumer surplus.

Lastly, in case 4, we examine the outcomes when both surge-pricing and a preferential algorithm are implemented. When comparing case 4 with case 2, we observe that the platform not only captures the entire consumer surplus, but it also further extracts driver surplus by introducing the preferential algorithm. As a consequence, the total driver surplus decreases from 21.56 to 16. On the other hand, when comparing case 4 with case 3, we observe that after implementing the preferential algorithm, the additional introduction of surge-pricing actually leads to an increase in driver surplus. This is because the platform serves more consumers, leading to drivers benefiting from the increased demand. Consequently, the total driver surplus increases from 12.5 to 16 between case 3 and case 4.

In summary, the findings show that both surge-pricing and the preferential algorithm contribute to increasing the platform's profit, but they operate through distinct mechanisms. By implementing surge-pricing, the consumer surplus is reduced compared to the baseline scenario; however, both the platform's profit and drivers benefit from this strategy. On the other hand, implementing the preferential algorithm may decrease driver surplus compared to the baseline scenario, but it leads to improved profitability for the platform and greater benefits for consumers. The results from case 4 demonstrate the complementarity between surge-pricing and the preferential algorithm. When both methods are implemented, the platform's profit is the highest, and the total surplus is also maximized. This highlights the strong synergy between surge-pricing and the preferential algorithm in achieving the best overall outcomes for the platform. However, it is important to note that this combination also results in a significant distributional effect, leading to a reduction in both consumer and driver surplus compared to the baseline scenario.

B Drivers' Finite-Horizon Dynamic Problem

This appendix describes in detail drivers' finite-horizon dynamic choices. For each hour t, the utility of working and not working are specified as

$$\begin{aligned}
U_{1t}^{\tau} &= \underbrace{W_t^{\tau}}_{\text{preferential wage rate}} + \sigma \cdot \epsilon_{1t}, \\
U_{0t}^{\tau} &= \underbrace{O_t^{\iota}}_{\substack{\text{outside option value,} \\ O_t^{\iota} = O_t + \eta_{\iota,t}}} + \sigma \cdot \epsilon_{0t},
\end{aligned} \tag{B.1}$$

Drivers first observe random shocks ϵ, and then decide whether to work or not.

B.1 Low-Performing Drivers

For the final period, $t = T$,

$$V_T^L = \begin{cases} W_T^L + \sigma \cdot \epsilon_{1T} & \text{if } a_T = 1 \ \& \ a_{T-1} = 1, \\ W_T^L - \kappa + \sigma \cdot \epsilon_{1T} & \text{if } a_T = 1 \ \& \ a_{T-1} = 0, \\ O_T + \sigma \cdot \epsilon_{0T} & \text{if } a_T = 0. \end{cases}$$

So, the expected utility for the last period T is given by

$$\begin{aligned}
EV_{1T}^L &= \sigma \left[\ln \Big(\exp(W_T^L/\sigma) + \exp(O_T/\sigma) \Big) + \gamma \right], \\
EV_{0T}^L &= \sigma \left[\ln \Big(\exp((W_T^L - \kappa)/\sigma) + \exp(O_T/\sigma) \Big) + \gamma \right].
\end{aligned}$$

Throughout our model, EV's subscript 1 represents $a_{t-1} = 1$. In this case, EV_{1T}^L represents the expected value of a low-performing driver at time T if $a_{T-1} = 1$.

At any time $t \in [T-1, 2]$,

$$V_t^L = \begin{cases} W_t^L + \sigma \cdot \epsilon_{1t} + \beta EV_{1t+1}^L & \text{if } a_t = 1 \ \& \ a_{t-1} = 1, \\ W_t^L - \kappa + \sigma \cdot \epsilon_{1t} + \beta EV_{1t+1}^L & \text{if } a_t = 1 \ \& \ a_{t-1} = 0, \\ O_t + \sigma \cdot \epsilon_{0t} + \beta EV_{0t+1}^L & \text{if } a_t = 0. \end{cases}$$

So, the expected utility of period t is given by

$$EV_{1t}^L = \sigma \left[\ln \Big(\exp((W_t^L + \beta EV_{1t+1}^L)/\sigma) + \exp((O_t + \beta EV_{0t+1}^L)/\sigma) \Big) + \gamma \right],$$
$$EV_{0t}^L = \sigma \left[\ln \Big(\exp((W_t^L - \kappa + \beta EV_{1t+1}^L)/\sigma) + \exp((O_t + \beta EV_{0t+1}^L)/\sigma) \Big) + \gamma \right].$$

For the first period, $t = 1$,

$$V_1^L = \begin{cases} W_1^L - \kappa + \sigma \cdot \epsilon_{11} + \beta EV_{12}^L & \text{if } a_1 = 1, \\ O_1 + \sigma \cdot \epsilon_{01} + \beta EV_{02}^L & \text{if } a_1 = 0. \end{cases}$$

The expected value of being a low-performing driver is then derived as

$$EV^L = \sigma \left[\ln \Big(\exp((W_1^L - \kappa + \beta EV_{12}^L)/\sigma) + \exp((O_1 + \beta EV_{02}^L)/\sigma) \Big) + \gamma \right]. \tag{B.2}$$

B.2 High-Performing Drivers

High-performing drivers are required to work at T_0 and for at least 2 consecutive hours. T_0 can be any hour between 10AM–2PM and 7PM–5AM. There are 16 possible work schedules to choose from. For schedule $j \in \{1, \cdots, 16\}$ with committed working hours $[T_0, T_0 + 1]$:

If $T_0 + 2 < T$, then for the last period T,

$$V_T^j = \begin{cases} W_T^H + \sigma \cdot \epsilon_{1T} & \text{if } a_T = 1 \ \& \ a_{T-1} = 1, \\ W_T^H - \kappa + \sigma \cdot \epsilon_{1T} & \text{if } a_T = 1 \ \& \ a_{T-1} = 0, \\ O_T + \sigma \cdot \epsilon_{0T} & \text{if } a_T = 0. \end{cases}$$

The expected utility of period T is given by:

$$EV_{1T}^j = \sigma \left[\ln \Big(\exp(W_T^H/\sigma) + \exp(O_T/\sigma) \Big) + \gamma \right],$$
$$EV_{0T}^j = \sigma \left[\ln \Big(\exp((W_T^H - \kappa)/\sigma) + \exp(O_T/\sigma) \Big) + \gamma \right].$$

At $t \in [T_0 + 3, T - 1]$,

$$V_t^j = \begin{cases} W_t^H + \sigma \cdot \epsilon_{1t} + \beta EV_{1t+1}^j & \text{if } a_t = 1 \ \& \ a_{t-1} = 1, \\ W_t^H - \kappa + \sigma \cdot \epsilon_{1t} + \beta EV_{1t+1}^j & \text{if } a_t = 1 \ \& \ a_{t-1} = 0, \\ O_t + \sigma \cdot \epsilon_{0t} + \beta EV_{0t+1}^j & \text{if } a_t = 0. \end{cases}$$

The expected utility of period $t \in [T_0+3, T-1]$ is given by:

$$EV_{1t}^j = \sigma \left[\ln \Big(\exp((W_t^H + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma) \Big) + \gamma \right],$$
$$EV_{0t}^j = \sigma \left[\ln \Big(\exp((W_t^H - \kappa + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma) \Big) + \gamma \right].$$

At time T_0+2, because the driver commits to work at T_0 and T_0+1, $a_{T0+1} = 1$ with probability 1:

$$V_{T_0+2}^j = \begin{cases} W_{T_0+2}^H + \sigma \cdot \epsilon_{1T_0+2} + \beta EV_{1T_0+3}^j & \text{if } a_{T_0+2} = 1, \\ O_{T_0+2} + \sigma \cdot \epsilon_{0T_0+2} + \beta EV_{0T_0+3}^j & \text{if } a_{T_0+2} = 0. \end{cases}$$

At T_0+1, the high-performing driver has to work. The expected value at any T_0+1 is given by

$$EV_{1T_0+1}^j = W_{T_0+1}^H + \beta EV_{1T_0+2}^j + \sigma\gamma.$$

At period T_0, the expected value is

$$EV_{1T_0}^j = W_{T_0}^H + \beta EV_{1T_0+1}^j + \sigma\gamma,$$
$$EV_{0T_0}^j = W_{T_0}^H - \kappa + \beta EV_{1T_0+1}^j + \sigma\gamma.$$

At any time before T_0, $t \in [2, T_0-1]$, the expected utility is given by

$$EV_{1t}^j = \sigma \left[\ln \Big(\exp((W_t^H + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma) \Big) + \gamma \right],$$
$$EV_{0t}^j = \sigma \left[\ln \Big(\exp((W_t^H - \kappa + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma) \Big) + \gamma \right].$$

For period 1,

$$V_1^j = \begin{cases} W_1^H - \kappa + \sigma \cdot \epsilon_{11} + \beta EV_{12}^j & \text{if } a_1 = 1, \\ O_1 + \sigma \cdot \epsilon_{01} + \beta EV_{02}^j & \text{if } a_1 = 0. \end{cases}$$

The expected value of being a high-performing driver is then derived as

$$EV^j = \sigma \left[\ln \Big(\exp((W_1^H - \kappa + \beta EV_{12}^j)/\sigma) + \exp((O_1 + \beta EV_{02}^j)/\sigma) \Big) + \gamma \right]. \tag{B.3}$$

C Identification and Estimation

C.1 Identification

We start with the case without UH so that $O_t^\iota = O_t$. Denote $P_t^\tau(a_T = j|a_{T-1} = i) = P_t^\tau(j|i)$, where $i, j = 0, 1$ and $\tau = L, H$. We have

$$\log P_T^L(1|1) - \log P_T^L(0|1) = \frac{W_T^L - O_T}{\sigma} \tag{C.1}$$

$$\log P_T^L(1|0) - \log P_T^L(0|0) = \frac{W_T^L - O_T - \kappa}{\sigma} \tag{C.2}$$

which implies that

$$\frac{\kappa}{\sigma} = [\log P_T^L(1|1) - \log P_T^L(0|1)] - [\log P_T^L(1|0) - \log P_T^L(0|0)] \tag{C.3}$$

Similarly, H-type drivers have

$$\log P_T^H(1|1) - \log P_T^H(0|1) = \frac{W_T^H - O_T}{\sigma} \tag{C.4}$$

$$\log P_T^H(1|0) - \log P_T^H(0|0) = \frac{W_T^H - O_T - \kappa}{\sigma} \tag{C.5}$$

Combining (C.1) and (C.4) gives

$$\sigma = \frac{W_T^H - W_T^L}{[\log P_T^H(1|1) - \log P_T^H(0|1)] - [\log P_T^L(1|1) - \log P_T^L(0|1)]} \tag{C.6}$$

which implies that κ is identified following (C.3)

$$\kappa = (W_T^H - W_T^L)\frac{[\log P_T^L(1|1) - \log P_T^L(0|1)] - [\log P_T^L(1|0) - \log P_T^L(0|0)]}{[\log P_T^H(1|1) - \log P_T^H(0|1)] - [\log P_T^L(1|1) - \log P_T^L(0|1)]}$$

and O_T is identified following (C.1) or (C.4)

$$O_T = W_T^L - (W_T^H - W_T^L)\frac{\log P_T^L(1|1) - \log P_T^L(0|1)}{[\log P_T^H(1|1) - \log P_T^H(0|1)] - [\log P_T^L(1|1) - \log P_T^L(0|1)]}$$

When there is no UH, we have three unknown parameters O_T, σ, κ and four equatios that capture the observed CCPs $P_T^\tau(1|a_{T-1})$, where $a_{T-1} = 0, 1$ and $\tau = L, H$. Note that $P_T^\tau(1|a_{T-1})$ and the above defined odd-ratios $P_T^\tau(1|a_{T-1})/P_T^\tau(0|a_{T-1})$ capture the same amount of identifying information because $P_T^\tau(1|a_{T-1}) + P_T^\tau(0|a_{T-1}) = 1$. The system is overidentified using just the last period, which is clear because our identification steps don't involve (C.5).

When there is UH, we assume that

$$O_t^\iota = O_t + \eta_{\iota,t},$$

where $\eta_{\iota,t}$ represents time-interval-specific preference. Considering data from the last period, we have five unknown parameters $O_T, \eta_{(5)}, p_{(5)}, \sigma, \kappa$, where (5) denotes the 5-th UH type, and again four equations that capture the observed CCPs $P_T^\tau(1|a_{T-1})$, where $a_{T-1} = 0, 1$ and $\tau = L, H$. Obviously, data from the last period are insufficient for point identification. Combining the last two periods, we have six unknown parameters $O_T, O_{T-1}, \eta_{(5)}, p_{(5)}, \sigma, \kappa$ and eight equations. More specifically, the eight equations represent how the observe CCPs $\overline{P}_t^\tau(1|a_{t-1}) = (1-p_{(5)})P_t^\tau(1|a_{t-1}) + p_{(5)}P_{t,(5)}^\tau(1|a_{t-1})$, where $a_{t-1} = 0, 1$, $t = T-1, T$, and $\tau = L, H$, relate to the unknown parameters. In particular,

$$\overline{P}_T^\tau(1|a_{T-1}) = (1-p_{(5)})\frac{\exp(\frac{W_T^\tau - \kappa 1(a_{T-1}=0)}{\sigma})}{\exp(\frac{W_T^\tau - \kappa 1(a_{T-1}=0)}{\sigma}) + \exp(\frac{O_T}{\sigma})} \tag{C.7}$$

$$+ p_{(5)}\frac{\exp(\frac{W_T^\tau - \kappa 1(a_{T-1}=0)}{\sigma})}{\exp(\frac{W_T^\tau - \kappa 1(a_{T-1}=0)}{\sigma}) + \exp(\frac{O_T + \eta_{(5)}}{\sigma})} \tag{C.8}$$

$$\overline{P}_{T-1}^\tau(1|a_{T-2}) = (1-p_{(5)})\frac{\exp(\frac{W_{T-1}^\tau - \kappa 1(a_{T-2}=0) + \beta EV_{1T}^\tau}{\sigma})}{\exp(\frac{W_{T-1}^\tau - \kappa 1(a_{T-2}=0) + \beta EV_{1T}^\tau}{\sigma}) + \exp(\frac{O_{T-1} + \beta EV_{0T}^\tau}{\sigma})} \tag{C.9}$$

$$+ p_{(5)}\frac{\exp(\frac{W_{T-1}^\tau - \kappa 1(a_{T-2}=0) + \beta EV_{1T}^{\tau,(5)}}{\sigma})}{\exp(\frac{W_{T-1}^\tau - \kappa 1(a_{T-2}=0) + \beta EV_{1T}^{\tau,(5)}}{\sigma}) + \exp(\frac{O_{T-1} + \eta_{(5)} + \beta EV_{0T}^{\tau,(5)}}{\sigma})} \tag{C.10}$$

where the expected utility for the last period T is given by

$$EV_{a_{T-1}T}^\tau = \sigma\left[\ln\left(\exp(\frac{W_T^\tau - \kappa 1(a_{T-1}=0)}{\sigma}) + \exp(\frac{O_T}{\sigma})\right) + \gamma\right],$$

$$EV_{a_{T-1}T}^{\tau,(5)} = \sigma\left[\ln\left(\exp(\frac{W_T^\tau - \kappa 1(a_{T-1}=0)}{\sigma}) + \exp(\frac{O_T + \eta_{(5)}}{\sigma})\right) + \gamma\right]$$

Note that $\overline{P}_t^\tau(0|a_{t-1}) = 1 - \overline{P}_t^\tau(1|a_{t-1})$ does not provide additional identification power.

We can continue the identification process backward and identify all the remaining parameters. In summary, we can identify the model with UH as long as each type involves at least two periods.

C.2 Estimation

We follow our identification argument closely in estimating the model. For each hour t, the utility of working and not working are specified as

$$\begin{aligned} U_{1t}^{\tau} &= W_t^{\tau} + \sigma \cdot \epsilon_{1t}, \\ U_{0t}^{\tau} &= O_t^{\iota} + \sigma \cdot \epsilon_{0t} \\ &= O_t + \eta_{\iota,t} + \sigma \cdot \epsilon_{0t}. \end{aligned}$$

Denote π_s as the probability for individual driver i being the unobserved type ι. We make use of observed conditional choice probabilities to estimate the structural parameters. We first derive the conditional choice probability of working for each type of driver.

Low-performing Drivers

For the final period T, the conditional probability of working for each unobserved type ι is

$$\begin{aligned} P^L(a_T = 1 | a_{T-1} = 1, \iota) &= \frac{\exp(W_t^L/\sigma)}{\exp(W_t^L/\sigma) + \exp(O_T^L/\sigma)}, \\ P^L(a_T = 1 | a_{T-1} = 0, \iota) &= \frac{\exp((W_t^L - \kappa_T)/\sigma)}{\exp((W_t^L - \kappa_T)/\sigma) + \exp(O_T^L/\sigma)}. \end{aligned}$$

For any $t \in [2, T-1]$,

$$\begin{aligned} P^L(a_t = 1 | a_{t-1} = 1, \iota) &= \frac{\exp((W_t^L + \beta E V_{1t+1}^L)/\sigma)}{\exp((W_t^L + \beta E V_{1t+1}^L)/\sigma) + \exp((O_t^L + \beta E V_{0t+1}^L)/\sigma)}, \\ P^L(a_t = 1 | a_{t-1} = 0, \iota) &= \frac{\exp((W_t^L - \kappa_t + \beta E V_{1t+1}^L)/\sigma)}{\exp((W_t^L - \kappa_t + \beta E V_{1t+1}^L)/\sigma) + \exp((O_t^L + \beta E V_{0t+1}^L)/\sigma)}. \end{aligned}$$

For $t = 1$,

$$P^L(a_1 = 1, \iota) = \frac{\exp((W_1^L - \kappa_1 + \beta E V_{12}^L)/\sigma)}{\exp((W_1^L - \kappa_1 + \beta E V_{12}^L)/\sigma) + \exp((O_1^L + \beta E V_{02}^L)/\sigma)}. \tag{C.11}$$

High-performing Drivers

For any schedule $j \in \{1, \cdots, 16\}$, the conditional probability of working in the final period T is

$$P^j(a_T = 1|a_{T-1} = 1, \iota) = \frac{\exp(W_t^H/\sigma)}{\exp(W_t^H/\sigma) + \exp(O_T/\sigma)},$$
$$P^j(a_T = 1|a_{T-1} = 0, \iota) = \frac{\exp((W_t^H - \kappa_T)/\sigma)}{\exp((W_t^H - \kappa_T)/\sigma) + \exp(O_T/\sigma)}.$$

For any $t \in [T_0 + 3, T - 1]$, we have

$$P^j(a_t = 1|a_{t-1} = 1, \iota) = \frac{\exp((W_t^H + \beta EV_{1t+1}^j)/\sigma)}{exp((W_t^H + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma)},$$
$$P^j(a_t = 1|a_{t-1} = 0, \iota) = \frac{\exp((W_t^H - \kappa_t + \beta EV_{1t+1}^j)/\sigma)}{\exp((W_t^H - \kappa_t + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma)}.$$

At $t = T_0 + 2$, we have

$$P^j(a_t = 1|a_{t-1} = 1, \iota) = \frac{\exp((W_t^H + \beta EV_{1t+1}^j)/\sigma)}{\exp((W_t^H + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma)}.$$

At $t = T_0 + 1$, we have

$$P^j(a_t = 1|a_{t-1} = 1, \iota) = 1.$$

At $t = T_0$, we have

$$P^j(a_t = 1|a_{t-1} = 1, \iota) = 1,$$
$$P^j(a_t = 1|a_{t-1} = 0, \iota) = 1.$$

For any $t \in [2, T_0 - 1]$, we have

$$P^j(a_t = 1|a_{t-1} = 1, \iota) = \frac{\exp((W_t^H + \beta EV_{1t+1}^j)/\sigma)}{\exp((W_t^H + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma)},$$
$$P^j(a_t = 1|a_{t-1} = 0, \iota) = \frac{\exp((W_t^H - \kappa_t + \beta EV_{1t+1}^j)/\sigma)}{\exp((W_t^H - \kappa_t + \beta EV_{1t+1}^j)/\sigma) + \exp((O_t + \beta EV_{0t+1}^j)/\sigma)}.$$

At $t = 1$, we have

$$P^j(a_1 = 1, \iota) = \frac{\exp((W_1^H - \kappa_1 + \beta EV_{12}^j)/\sigma)}{\exp((W_1^H - \kappa_1 + \beta EV_{12}^j)/\sigma) + \exp((O_1 + \beta EV_{02}^j)/\sigma)}.$$

Therefore, at any t, the conditional probability for high-performing drivers is

$$\begin{aligned} P^H(a_t = 1|a_{t-1} = 0) &= \sum_{\iota} \sum_{j=1}^{16} \pi_\iota \cdot \widetilde{P}^j(\iota) \cdot P^j(a_t = 1|a_{t-1} = 0, \iota), \\ P^H(a_t = 1|a_{t-1} = 1) &= \sum_{\iota} \sum_{j=1}^{16} \pi_\iota \cdot \widetilde{P}^j(\iota) \cdot P^j(a_t = 1|a_{t-1} = 1, \iota), \end{aligned} \tag{C.12}$$

where $\widetilde{P}^j$ is the probability of choosing each high-performing schedule, and

$$\widetilde{P}^j(\iota) = \frac{\exp(EV^j(\iota))}{\sum_{k=1}^{16} \exp(EV^k(\iota))}.$$

The MSM estimate $\widehat{\boldsymbol{\theta}}$ minimizes the weighted distance between the data moments and the simulated moments:

$$L(\boldsymbol{\theta}) = arg \min_{\theta,\pi} \quad [\boldsymbol{P_\tau^d} - \boldsymbol{P_\tau^S}(\boldsymbol{\theta})]' W [\boldsymbol{P_\tau^d} - \boldsymbol{P_\tau^S}(\boldsymbol{\theta})],$$

where W is a positive definite matrix.

Denote the actual CCPs obtained from the data as $\boldsymbol{P_\tau^d}(\cdot)$, which is a 48-by-1 vector. Second, for a given set of parameters $\boldsymbol{\theta}$, the model-simulated CCPs are $\boldsymbol{P_\tau^S}(\cdot)$. The model is estimated by minimizing the weighted distance between the data moments and the simulated moments of the finite mixture model:

$$\{\hat{\theta}, \hat{\pi}\} = arg \max_{\theta,\pi} \sum_{i=1}^{N} \ln \left[\sum_{s} \pi_s \prod_{t=1}^{24} l(a_{it}|s, \hat{p}, a_{it-1}, \theta) \right],$$

where $\hat{p}$ is a vector of empirical conditional choice probabilities; π_s is the population probability of type s; the number of unobserved types is assumed to be known; and $l(a_{it}|s, \hat{p}, a_{it-1}, \theta)$ denotes the likelihood contribution of driver i at time t.

We can express the likelihood as follows:

$$l(a_{it}|s, \hat{p}, a_{it-1}, \theta) = \frac{a_{it} \exp\left((v_{1t}^\tau - v_{0t}^\tau)/\sigma\right) + (1 - a_{it})}{1 + \exp\left((v_{1t}^\tau - v_{0t}^\tau)/\sigma\right)}.$$

This can be estimated through a two-step estimator. First, we can calculate $\widehat{q}_{ns}$, the probability n is in unobserved state s, as

$$q_{ns}^{(m+1)} = \frac{\pi_s^{(m)} \prod_{t=1}^{24} l(a_{it}|s, \hat{p}, a_{it-1}, \theta)}{\sum_{s'} \pi_{s'}^{(m)} \prod_{t=1}^{24} l(a_{it}|s', \hat{p}, a_{it-1}, \theta)}.$$

Then, use $q_{ns}^{(m+1)}$ to compute $\pi_s^{(m+1)}$ according to

$$\pi_s^{(m+1)} = \frac{1}{N} \sum_{n=1}^{N} q_{ns}^{(m+1)}.$$

Next, use $q_{ns}^{(m+1)}$ to update $p^{(m+1)}$ from

$$P(a_{t+1} = 0|a_t = 0, s) = \frac{\sum_{n=1}^{N} d_{0nt} q_{ns}^{(m+1)}}{\sum_{n=1}^{N} q_{ns}^{(m+1)}}.$$

Taking $q_{ns}^{(m+1)}$ and $p^{(m+1)}$ as given, obtain $\theta^{(m+1)}$ from

$$\theta^{(m+1)} = arg \max_{\theta} \sum_{i=1}^{N} \sum_{s} \sum_{t=1}^{24} q_{ns}^{(m+1)} \ln \left[l(a_{it}|s, \hat{p}, a_{it-1}, \theta) \right].$$

We have 16 unknown high-performing types. First, we can calculate $\widehat{q}_{nsj}$, the probability n is in unobserved state s and schedule j, as

$$q_{nsj}^{(m+1)} = \frac{\pi_{sj}^{(m)} \prod_{t=1}^{24} l(a_{it}|s, \hat{p}, a_{it-1}, \theta, j)}{\sum_{s'} \sum_{j'} \pi_{s'j'}^{(m)} \prod_{t=1}^{24} l(a_{it}|s', \hat{p}, a_{it-1}, \theta, j)}.$$

Then, use $q_{nsj}^{(m+1)}$ to compute $\pi_{sj}^{(m+1)}$ according to

$$\pi_{sj}^{(m+1)} = \frac{1}{N} \sum_{n=1}^{N} q_{njs}^{(m+1)}.$$

Next, use $q_{nsj}^{(m+1)}$ to update $p^{(m+1)}$ from

$$P(a_{t+1} = 0|a_t = 0, s, j) = \frac{\sum_{n=1}^{N} d_{0nt} q_{nsj}^{(m+1)}}{\sum_{n=1}^{N} q_{nsj}^{(m+1)}}.$$

Taking $q_{ns}^{(m+1)}$ and $p^{(m+1)}$ as given, obtain $\theta^{(m+1)}$ from

$$\theta^{(m+1)} = arg\max_{\theta} \sum_{i=1}^{N} \sum_{s} \sum_{j} \sum_{t=1}^{24} q_{nsj}^{(m+1)} \ln \left[l(a_{it}|s, \hat{p}, a_{it-1}, \theta, j) \right].$$

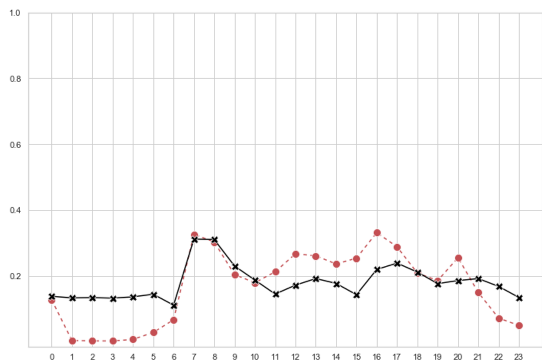
Similarly, we derive the conditional probability for high-performing drivers for each schedule. Because sixteen possible work schedules satisfy the high-performing requirement, at any time t, the conditional probability for high-performing drivers is

$$\begin{aligned} P_H(a_t = 1|a_{t-1} = 0) &= \sum_{j=1}^{16} \widetilde{P}_j \cdot P_j(a_t = 1|a_{t-1} = 0), \\ P_H(a_t = 1|a_{t-1} = 1) &= \sum_{j=1}^{16} \widetilde{P}_j \cdot P_j(a_t = 1|a_{t-1} = 1), \end{aligned} \tag{C.13}$$

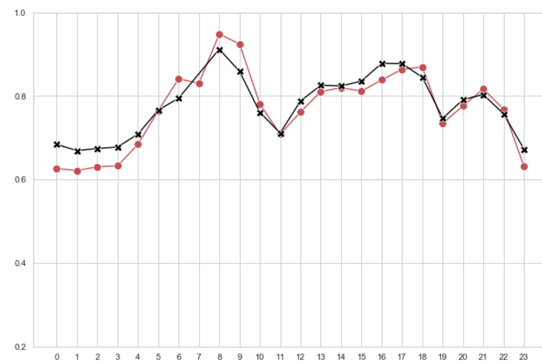
where $\widetilde{P}_j$ is the probability of choosing schedule j within high-performing drivers. Therefore, equations **??** and C.13 show the model-predicted CCPs as a function of observed wage sequence $\{\boldsymbol{W^H}, \boldsymbol{W^L}\}$ and parameters $\boldsymbol{\theta}$. In Appendix **??**, we show the detailed derivation of $P_\tau(a_t = 1|a_{t-1} = 0)$ and $P_\tau(a_t = 1|a_{t-1} = 1)$ for $\tau \in \{L, H\}$ and $t \in [1, 24]$.

D Model Validation

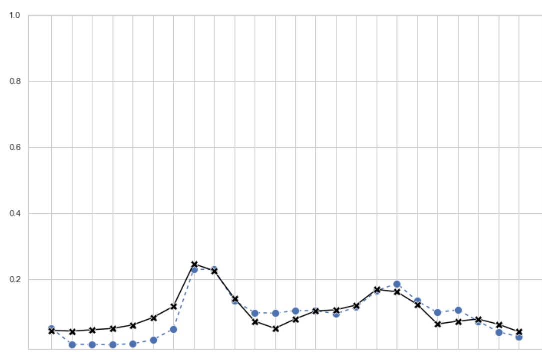
Figure D.1 illustrates the model's goodness of fit. The simulated conditional choice probabilities (CCPs) reasonably align with the observed CCPs for both high-performing and low-performing drivers. However, there is a slight discrepancy in the fit of high-performing drivers at $a_{t-1} = 0$ during early-morning hours. This discrepancy could be attributed to the relatively low number of transactions occurring during early-morning compared to other working hours.



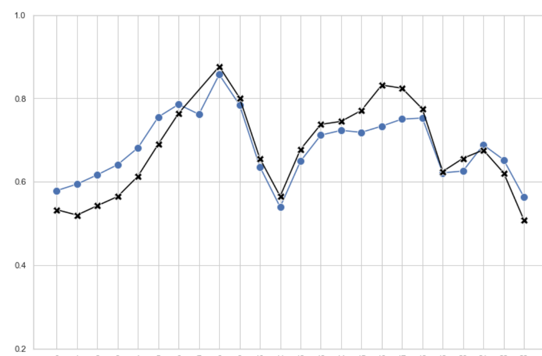
(a) High-performing Drivers, State = 0



(b) High-performing Drivers, State = 1



(c) Low-performing Drivers, State = 0



(d) Low-performing Drivers, State = 1

Figure D.1: Model Goodness of Fit

Note: Figure D.1 shows the model's simulated values against the empirically observed CCPs. The black lines represent the model's simulated values.

Online Appendices: Not For Publication

E Data Description

For the working dataset, we are interested in driver operation and wage information, and construct several important variables for each driver-hour:

- **Earning time** is the trip duration, measured as the amount of time a driver spends with the rider. A driver can transport riders and collect revenue only during the earning time.
- **Drive Distance** measures the distance over which a driver serves a rider in an hour.
- **Driver's Hourly Wage** measures the revenue of a driver in an hour.[31] Given that the platform fee is around 20% of the revenue, the driver income is roughly 80% of the ride fare.
- **Pickup Time** measures the time a driver spends on the way to pick up riders.
- **Idle Time** is the time a driver spends waiting for orders in an hour, given by the following relationship: Idle time = 60 - Work time - Pickup time.
- **Number of Orders** measures the number of orders a driver receives in an hour.[32]

Below, we discuss our algorithm of how we construct a driver-hour level dataset from the driver-rider-order level dataset:

- **Drop Outliers.** We keep all orders with departure and arrival in the urban area (eight districts) within the city, and drop orders with a price of zero, a price above 200, or that span over four hours. In total, we drop less than 0.5% of the observations.
- **Construct Work Schedules.** Following Chen et al. (2019), we define a driver as working in an hour t if he works at least ten minutes out of the hour. At night (22PM–6AM), when orders are sparse, we define a driver as working in hour t if he/she works at hour $t-1$ as well as hour $t+1$. All working hours of a driver comprise his/her work schedule.

[31] Our definition is different from Chen et al. (2019), which defines "wage rate" as a driver's total earnings in an hour, divided by minutes worked, multiplied by sixty. In other words, they study the wage rate when the driver is driving a rider, and we focus on the wage rate when the driver is active on the platform.

[32] In rare cases, an order may span several hours, which we attribute to the hour of departure.

- **Match Order to Hour.** Suppose an order spans x hours. We divide this order into x sub-orders, with each sub-order corresponding to an hour. The hourly wage rate and driving distance are defined to be proportional to each hour. For instance, suppose an order starts at 8:50 and finishes at 9:20, yielding a revenue of 60 CCY. We say that $\frac{10}{10+20} = \frac{1}{3}$ of the order belongs to 8 AM operations, and the rest contributes to 9 AM operations. By doing so, we divide this order into two sub-order operations: The driver drives 10 minutes and earns 20 CCY at 8 AM and drives 20 minutes (10 miles) and makes 40 CCY at 9 AM. After matching orders to hours, we aggregate all sub-orders in an hour and obtain this driver's earning time, ride prices, pickup time, idle time, and number of orders in this hour.

F Summary Statistics: Orders and Transactions

Table F.1 summarizes orders and transactions, and the unit of observation is at the order level. There are a total of around 15 million order transactions in our sample period, with an average route length of 6.9 km and drive time of 17 minutes. The average price per order is 25.31 CCY (about $4 USD).

Table F.1: Summary Statistics: Orders and Transactions

Variable	Mean	Std. Dev.	Min	Max
Price	25.31	26.44	0	3,387
Drive Distance (km)	6.92	6.85	0	727
Drive Time (minutes)	17.36	13.14	0	1,458
Number of Observations		14,471,573		

Multi-Homing versus Single-Homing. In our main analysis, we focus on Platform X, because Platform X accounts for more than 90% of China's mainland ride-hailing market. Nonetheless, there is a concern that drivers may switch between working for different platforms if they pay different hourly wages. To address such concerns, we document the number of vehicles/drivers that are multi-homed versus single-homed in our data. First, we look at the number of vehicles that are multi-homed from registration data. Panel (a) of Table F.2 shows that 85% of vehicles are registered to only one platform, and only 1.8% of vehicles are registered to more than two platforms. Therefore, multi-homing is not very common based on vehicle registration information. Then, we look at how common multi-homing is directly from actual transactions. Panel (b) of Table F.2 shows that among all the vehicles that conducted business in December 2018, 92.5% used a single platform and never switched to another platform within the month. Only 0.3% of vehicles used more than two platforms in the given month. The evidence shows that the majority of vehicles/drivers are single-homed.

Table F.2: Multi-Homing versus Single-Homing

Number of Registered Platforms	Number of Vehicles	Percent
1	86,422	84.6%
2	13,838	13.5%
3	1,866	1.8%

(a) Based on Vehicle Registration Data

Number of Used Platforms	Number of Vehicles	Percent
1	49,213	92.5%
2	3,836	7.2%
3	141	0.3%

(b) Based on Transactional Data

Among the multi-homed drivers, we further study how these drivers switch between different ride-sharing platforms. We also calculate the number of multi-homed and single-homed drivers within a whole day based on actual transactions. In any given day of December, only about 1% of drivers used more than one platform within a day. This therefore suggests that drivers in our data are mostly single-homed and rarely switch between platforms.

Orders, Transactions, Precipitation, and Temperature. Figure F.1 reports the daily number of orders and transactions during our sample period (10 days of order data and 31 days of transaction data). We compare them with daily precipitation and average temperatures. From December 6$^{\text{th}}$ to 10$^{\text{th}}$, the precipitation increases and temperature decreases, resulting in more ride orders (customer demand). However, the number of completed transactions across days remains the same throughout our sample period. Information about precipitation and temperature is used in our demand estimation.

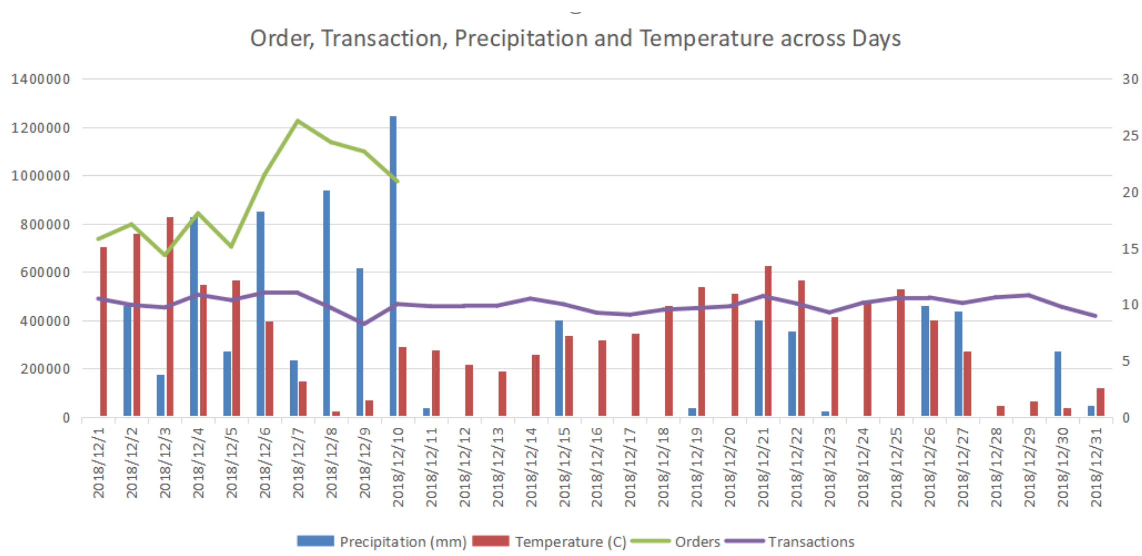


Figure F.1: Orders, Transactions, Precipitation, and Temperature across Days

G Additional Regression Tables on Wage Differentials

Appendix G contains additional regression tables for robustness checks, and verifies driver demographics that may have explanatory power for wage differentials. Table G.1 reports how the driver's hourly wage depends on the fraction of different time intervals. We find that drivers' hourly wages are higher when they work more during midday and at night. Table G.2 shows that, given their work schedule, there is little evidence of wage differentials based on driver demographics. Indeed, including driver characteristics barely changes the R-squared. Moreover, a one standard-error change in the fraction of incentivized hours changes wage rate by 14, which is an order of magnitude higher than the most important demographic variable, age. Despite the statistical significance of gender, it is economically insignificant in determining wage rate. In contrast, the coefficients on birth city and age reflect work schedule variation across driver groups conditioning on the first two variables. These results motivate controlling for age and birth city in our empirical analysis.

Table G.1: Hourly Wage by Different Schedules

Dependent Variables	Hourly Wage			
	(1)	(2)	(3)	(4)
# of Work Hours in month	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
% Morning Hours	-15.895***			
	(0.185)			
% Midday Hours		0.753***		
		(0.148)		
% Afternoon Hours			-14.407***	
			(0.284)	
% Night Hours				11.131***
				(0.119)
Constant	55.882***	54.823***	56.358***	51.137***
	(0.126)	(0.127)	(0.129)	(0.132)
Observations	4,182,318	4,182,318	4,182,318	4,182,318
R-squared	0.042	0.040	0.041	0.042

Notes: We control for day-hour fixed effects, origin district fixed effects, and destination district fixed effects. Standard errors are in parentheses. *** p<0.01.

Table G.2: Hourly Wage by Driver Characteristics

Dependent Variables	Hourly Wage				Coef × Std
	(1)	(2)	(3)	(4)	(5)
# of Work Hours in month	0.003***	0.003***	0.004***	0.003***	0.818
	(0.000)	(0.000)	(0.000)	(0.000)	
% Incentivized Hours		18.724***		18.216***	14.042
		(0.170)		(0.171)	
Non-local			-0.332***	-0.138***	-0.097
			(0.036)	(0.027)	
Age			-0.061***	-0.045***	-1.689
			(0.001)	(0.001)	
Female			-0.677***	-0.431***	-0.009
			(0.081)	(0.081)	
Constant	54.918***	39.201***	57.419***	41.342***	
	(0.126)	(0.190)	(0.141)	(0.203)	
Day FE	Y	Y	Y	Y	
Hour FE	Y	Y	Y	Y	
Origin FE	Y	Y	Y	Y	
Destination FE	Y	Y	Y	Y	
Observations	4,182,331	4,182,331	4,182,318	4,182,318	
R-squared	0.040	0.043	0.041	0.043	

Notes: We control for day-hour fixed effects, origin district fixed effects, and destination district fixed effects. Standard errors are in parentheses. *** p<0.01.

H Cluster Schedules and Hourly Rates

This online appendix describes how we cluster drivers using their work schedule and hourly wage rate data. We use the data that contains driver schedules and hourly revenue for all drivers on Dec. 3rd, 2018. Our sample includes 23,689 drivers (observations).

We use a 24×1 vector for each driver to describe their working schedule and hourly wage rate. The n^{th} element represents the hourly revenue at n o'clock. If the driver does not work at this hour, we denote the element value to be 0. For instance, if the driver worked at 7 AM and earned 18 CNY, the 7th element is 18 for this vector. In addition, we construct the following variables to measure the driver's working schedule and include them in our study:

- **earlymorning**: driver's working hours during early morning (0 - 7)
- **morning**: driver's working hours during morning peak (7 - 10)
- **midday**: driver's working hours during mid-day (10 - 16)
- **afternoon**: driver's working hours during afternoon (16 - 19)
- **evening**: driver's working hours during evening (19 - 22)
- **night**: driver's working hours during night (22 - 24)
- **workhour**: driver's working hours in one day
- **start**: the hour in which the driver starts work
- **end**: the hour in which the driver ends work
- **consecutive**: driver's consecutive working hours in a day
- **consecutive1/2/3**: We divide 24 hours into 3 parts. Consecutive1/2/3 indicates a driver's consecutive working hours in each part of the day.
- **consecutive4**: driver's consecutive working hours during evening (19 - 22)
- **morningCon/afternoonCon**: driver's consecutive working hours during morning and afternoon hours
- **HourlyRate**: driver's average hourly wage rate in a day

We apply the k-means method and cluster the drivers in our working database. The purpose of this clustering is to explore how different work schedules can affect the driver's hourly revenue. The k-means clustering method divides observations into a certain number (k) of groups according to their similarity. We do not know the number of groups we define *ex ante* . Therefore, we have tried $k = 2, 3, 4$ different clusters.

Table 1 illustrates the results when $k = 2$. Drivers are divided into low hourly rates (cluster 1) and high hourly rates (cluster 2). High hourly rate drivers are more likely to work longer and consecutive hours. Tables 2 and 3 report cluster results for $k = 3$ and $k = 4$, respectively. Though we pre-set more clusters, drivers can be separated into two groups. When $k = 3$, we have low hourly rate drivers (cluster 1) and high hourly rate drivers (clusters 2 and 3). When $k = 4$, we have low hourly rate drivers (cluster 1) and high hourly rate drivers (clusters 2, 3, and 4). Moreover, no matter which k we choose, the characteristics of the lower-income schedules are similar: they work shorter and fewer consecutive hours.

Table H.1: Clustering results for k=2

	cluster1	cluster2
Count	11,226	12,472
earlymorning	0.59	0.29
morning	1.2	2.15
midday	1.61	4.86
afternoon	0.93	2.71
evening	0.87	2.16
night	0.7	1.46
workhour	5.62	13.01
start	9.21	7.4
end	16.59	20.92
consecutive	4.56	11.59
consecutive1	1.3	1.61
consecutive2	2.16	6.24
consecutive3	1.91	4.75
consecutive4	1.29	2.98
morningCon	1.56	2.95
afternoonCon	1.22	3.52
HourlyRate	40.03	46.91

Table H.2: Clustering results for k=3

	cluster1	cluster2	cluster3
Count	8,912	7,745	7,041
earlymorning	0.51	0.52	0.27
morning	1.21	1.43	2.51
midday	1.46	3.42	5.38
afternoon	0.76	2.58	2.48
evening	0.6	2.89	1.43
night	0.43	2.51	0.59
workhour	4.79	12.37	12.34
start	9.36	8.07	7.14
end	15.57	22.51	19.35
consecutive	3.92	10.36	11.35
consecutive1	1.24	1.34	1.83
consecutive2	1.98	4.4	6.91
consecutive3	1.34	6.16	3.27
consecutive4	0.84	4.41	1.7
morningCon	1.56	1.98	3.42
afternoonCon	0.98	3.52	3.11
HourlyRate	38.28	47.73	46.12

Table H.3: Clustering results for k=4

	cluster1	cluster2	cluster3	cluster4
Count	7,921	6,246	5,328	4,203
earlymorning	0.48	0.24	0.27	0.82
morning	1.32	2.59	2.36	0.3
midday	1.41	4.73	5.37	2.11
afternoon	0.72	2.79	2.33	2.16
evening	0.46	2.9	0.98	2.75
night	0.28	2.26	0.23	2.46
workhour	4.55	14.55	11.4	9.67
start	9.12	6.87	7.32	9.77
end	14.93	22.27	18.54	22.47
consecutive	3.71	12.44	10.53	8.16
consecutive1	1.29	1.82	1.72	0.96
consecutive2	1.94	6.09	6.85	2.76
consecutive3	1.09	6.04	2.51	5.74
consecutive4	0.62	4.19	1.06	4.26
morningCon	1.69	3.51	3.25	0.47
afternoonCon	0.91	3.74	2.85	3.02
HourlyRate	37.54	46.78	45.77	48.05

I Results from Eliminating the Wage Differential

To understand the effect of eliminating wage differentials between high-performing and low-performing drivers in the short run, Figure I.1 shows the equilibrium labor supply decision in panel (a) and the equilibrium wage rate in panel (b). In the short term, the ride fares are held fixed. When we eliminate the wage differential between high-performing and low-performing drivers, drivers will switch away from being high-performing because there is no longer any bonus for high performance. Because we fix the ride fares, and hence rider demand in the short run, there will be a labor shortage because of fewer high-performing drivers. As a result of the excess demand, the equilibrium wage rate without a preferential algorithm will be higher than the wage rate of low-performing drivers when there is a preferential algorithm. The equilibrium wage rate without a preferential algorithm lies between the former wage rate of high-performing and low-performing drivers.

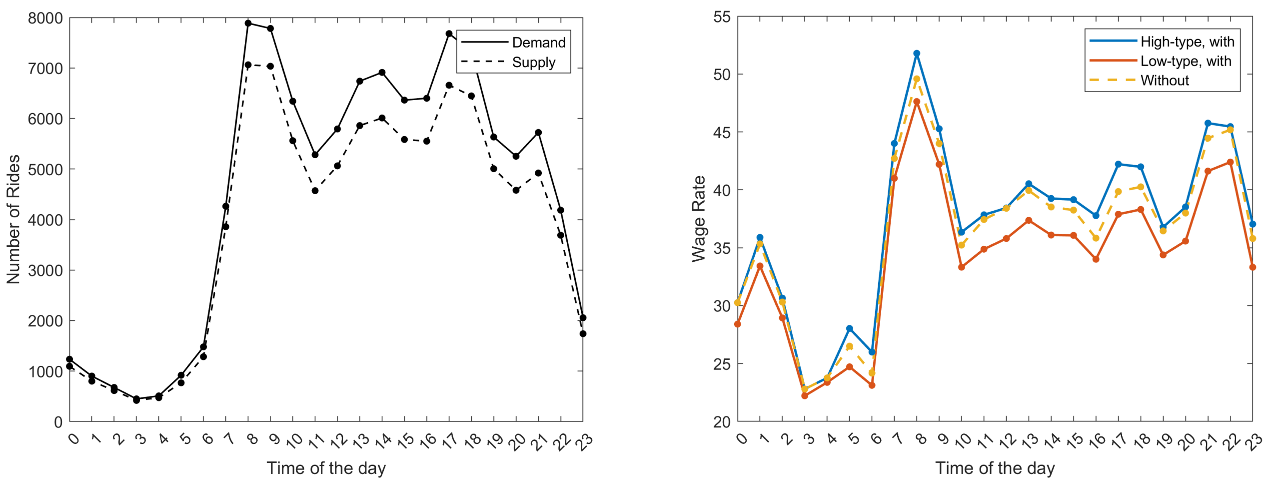
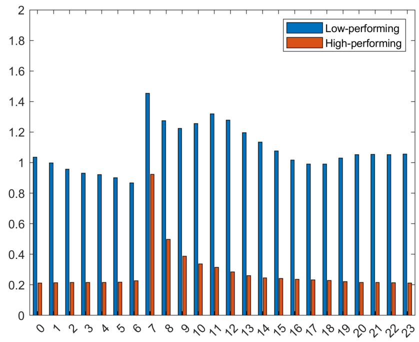
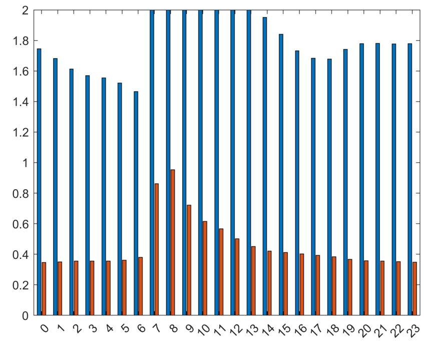


Figure I.1: Results from Eliminating the Wage Differential between W^H and W^L

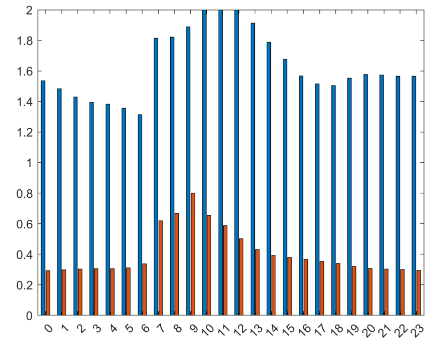
Next, we study the counterfactual results of eliminating the wage differential between high-performing and low-performing drivers only in the treatment hour h. When we eliminate the wage differential between high-performing and low-performing drivers in one particular hour, drivers will switch away from being high-performing, because the benefit for being a high-performing driver is now smaller. Because we fix the ride fares, and hence rider demand in the short run, there will be a labor shortage because of fewer high-performing drivers. As a result, the equilibrium wage rate for low-performing drivers without a preferential algorithm will be higher compared to the wage rate when there is a preferential algorithm. Figure I.2 shows the elasticity of labor supply corresponding to the elimination of the wage differential of treatment hour h.



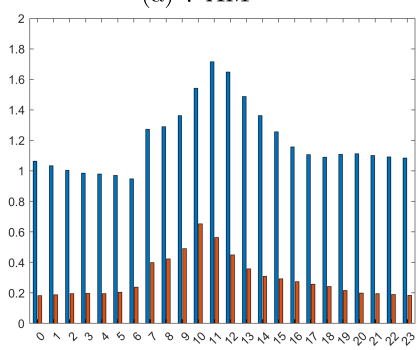
(a) 7 AM



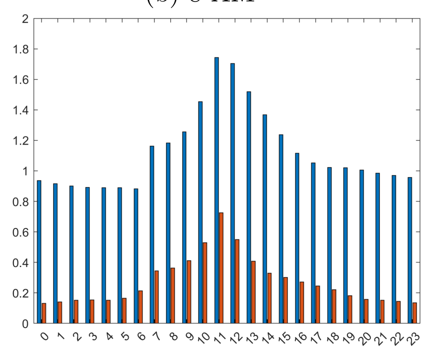
(b) 8 AM



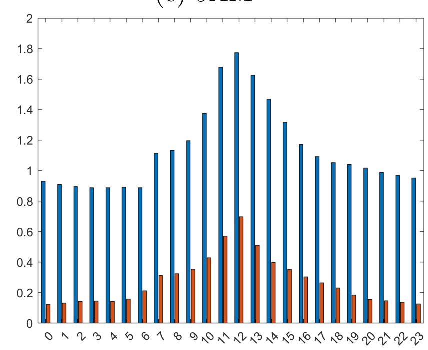
(c) 9AM



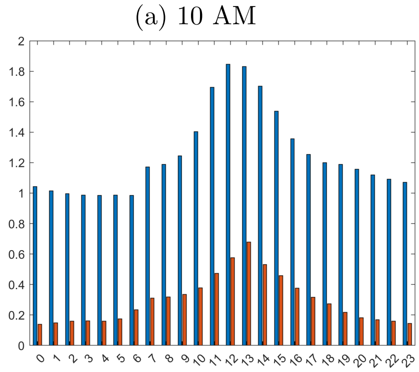
(a) 10 AM



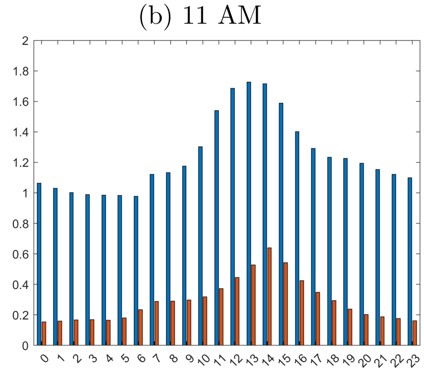
(b) 11 AM



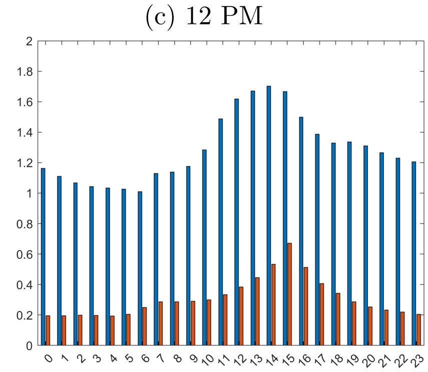
(c) 12 PM



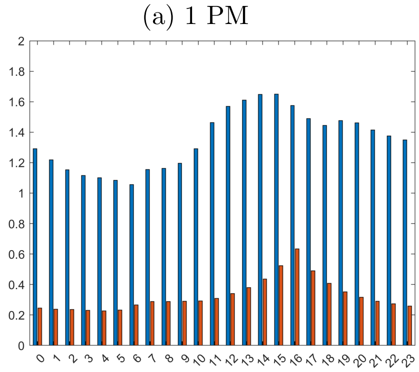
(a) 1 PM



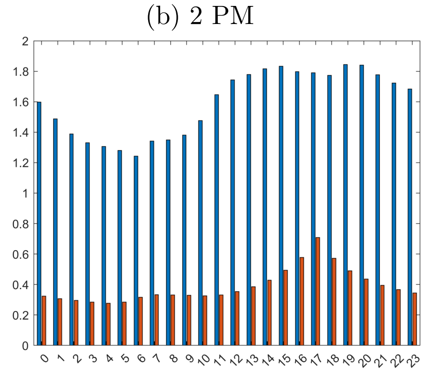
(b) 2 PM



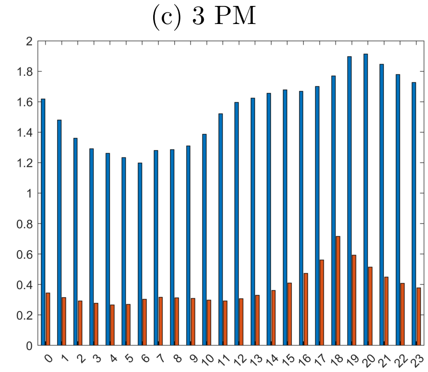
(c) 3 PM



(a) 4 PM



(b) 5 PM



(c) 6 PM

Figure I.2: Absolute Elasticity of Low-Performing and High-performing Drivers

J Explore Order Assignment using Detailed Order Information

This section explores platform order assignment using detailed order information. We first divide the city into 1km by 1km grids so that we can better locate these drivers. We compare order quantity and quality for drivers who finish their last trip in the same grid at around the same time. We find high-performing drivers are more likely to receive assignments for higher-priced orders and have less idle time waiting for the driver.

We explore the order fare and wait time for different drivers who complete their last trip in approximately the same time in the same grid. Table J.1 shows that high-performing drivers receive orders which are 4.15% more expensive compared to low-performing drivers (Column 2). In addition, high-performing drivers wait 1.45% less time for the next order (Column 4). These empirical findings are consistent with the platform favoring high-performing drivers: assigning them with orders with higher revenue and less wait time.

Table J.1: Order Fare and Wait Time

	(1)	(2)	(3)	(4)
	Order Fare	log(Order Fare)	Idle Time	log(Idle Time)
High-performing	0.0437***	0.0415***	-0.267***	-0.0145***
	(0.00127)	(0.00126)	(0.0273)	(0.00237)
Constant	3.432***	3.018***	8.913***	1.292***
	(0.0162)	(0.00120)	(0.0260)	(0.00225)
Observations	3,081,466	3,081,466	3,058,969	3,058,969
R-squared	0.073	0.103	0.339	0.223

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

We control for 15Minute $\times$ 1km $\times$ 1km Grid fixed effects.

K Control For Unobservable Selection: IV results

To mitigate potential biases in driver selection based on unobservable characteristics, we have employed instrumental dummy variables: the rate of change in precipitation and air quality index (AQI) in the driver's hometown city between 2017 and 2018. The selection of drivers based on these variables is not influenced by the drivers' unobserved characteristics.

These weather variables satisfy the two conditions required for valid instrumental variables (IVs). Firstly, the occurrence of precipitation and changes in air pollution may be correlated with a driver's decision to become a high-performing driver, as suggested by (Miguel et al., 2004). For instance, alterations in precipitation and air pollution might motivate more drivers to leave their hometowns and become high-performing drivers in the focal city under study. Secondly, the variation in weather conditions in a driver's hometown should not directly impact the driver's hourly rate or order distribution in the city being studied. The IV results are presented in column (5), revealing a more significant wage differential between high-performing and low-performing drivers. For further details and additional IV results, please refer to Section K.

Table K.1: Wage Differential: First Stage

	High-performing					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Precipitation	-0.157***	-0.155***	-0.154***	-0.159***	-0.157***	-0.155***
	(0.00131)	(0.00129)	(0.00130)	(0.00134)	(0.00132)	(0.00132)
Change in AQI				-0.0270***	-0.0231***	-0.0206***
				(0.00322)	(0.00318)	(0.00318)
Constant	0.898***	0.898***	0.886***	0.895***	0.896***	0.884***
	(0.000148)	(0.000146)	(0.000450)	(0.000327)	(0.000324)	(0.000529)
Controls:						
Day-Hour FE		Y	Y		Y	Y
Origin/Dest FE			Y			Y
Observations	4,182,318	4,182,318	4,182,318	4,182,318	4,182,318	4,182,318
R-squared	0.003	0.023	0.024	0.003	0.023	0.024

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The first stage results are presented in Table K.1. We regress the High-performing dummy on the weather conditions, with F-values exceeding 1000 for all specifications. In column (1), we regress the High-performing dummy on the precipitation change without any fixed effects. In column (2), we include day-hour fixed effects, and in column (3), we include day-hour fixed effects as well as origin and destination fixed effects. Columns (4)-(6) are replicates of (1)-(3) except that we include both precipitation change and AQI change as explanatory variables.

Table K.2: Wage Differential: IV results

	Hourly Wage					
	(1)	(2)	(3)	(4)	(5)	(6)
High-performing	8.908***	9.480***	5.599***	9.268***	9.813***	5.759***
	(0.679)	(0.676)	(0.677)	(0.678)	(0.675)	(0.676)
Constant	41.98***	47.28***	49.47***	41.65***	46.97***	49.32***
	(0.611)	(1.192)	(1.186)	(0.609)	(1.191)	(1.185)
Day-Hour FE		Y	Y		Y	Y
Origin FE			Y			Y
Destination FE			Y			Y
IV (2017-2018)						
Change in Precipitation	Y	Y	Y	Y	Y	Y
Change in AQI				Y	Y	Y
Observations	4,182,318	4,182,318	4,182,318	4,182,318	4,182,318	4,182,318
R-squared	0.024	0.034	0.050	0.024	0.034	0.050

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Our analysis reveals a robust negative correlation between precipitation and driver performance. Specifically, a one percent increase in precipitation in a driver's hometown is found to be associated with a 0.154% decrease in the probability of a driver attaining high-performance status. More precipitation usually associates with higher agricultural output (Miguel et al., 2004) and inadvertently diminish drivers' incentives to move to the city we study and become a high-performing driver. Moreover, we identify a negative impact of air quality on driver performance. A one percent increase in the Air Quality Index (AQI), reflecting elevated pollution levels, corresponds to a 0.02% decrease in the likelihood of drivers achieving high-performance status. This observation aligns with the hypothesis that heightened pollution levels, often linked to increased industrial output in drivers' hometowns, may undermine their motivation to move to the city we study and become a high-performing driver.

The instrumental variable (IV) results are presented in Table K.2. Column (1) presents the results without any fixed effects, while column (2) includes day-hour fixed effects. In column (3), we include day-hour fixed effects, origin fixed effects, and destination fixed effects. Columns (4)-(6) are replicates of (1)-(3) except that we include both precipitation change and AQI change as instrument.

Our findings demonstrate that high-performing drivers outearn their low-performing counterparts. Specifically, when examining column (3)/(6), we observe that high-performing drivers earn an additional 5.6/5.8 CCY per hour compared to low-performing drivers. This wage differential is notably higher than what is indicated by our main ordinary least squares (OLS) findings.

We propose a conjecture that low-performing drivers exhibit a higher level of strategic behavior. For instance, they may strategically select optimal times and locations to work, which contributes to their comparatively lower number of working hours. This aligns with the fact that their working decisions are more discerning and selective. In summary, our OLS estimates underestimate the wage disparity due to algorithmic preferences.