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

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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

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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 1.62%, 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 4.12%. 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 3 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 A Simple Example

Consider a simple economy with two periods to demonstrate intertemporal labor supply and the platform's incentive for using a preferential algorithm. There are four passengers in the morning and two in the afternoon. Each trip generates $5 in revenue, with the platform taking $1 representing the average commission rate of 20% in our data. Gas and other costs are worth $3, leaving a $1 driver profit per trip. Two drivers, Jack and Rose, can each complete three trips per half day. They have different lifestyles and hence derive different value from alternative activities other than driving passengers. Table 1 shows their outside option values. We set Rose's outside option value for the afternoon sufficiently high so we can focus on motivating Jack to work. Drivers choose when to work freely, and the platform's algorithm decides trip assignments for active drivers. Given the demand and supply, the platform prefers for everyone to work in the morning and, most importantly, Jack to work full-time (both in the morning and afternoon). We now demonstrate that the platform is better off with a preferential algorithm that favors Jack in the morning.

Under a "fair" assignment, the platform assigns trips equally, and each driver gets two trips in the morning. Table 2 demonstrates Jack's choices and payoffs. Without a preferential

Table 1: Drivers' Outside Option Values

	AM	PM
Jack	1	3
Rose	1	88

algorithm, Jack will earn \$2 in pro t working in the afternoon. However, he su ers a loss of \$1 when the outside option value is \$3 in the afternoon. Therefore, Jack has no incentive to work in the afternoon because of his high outside option value. Instead, consider a preferential algorithm that gives Jack three trips instead of two in the morning if he works full time and one trip otherwise, and let Rose complete the remaining trips. By working in the afternoon, Jack forgoes the outside option valued at \$3. As a result, he su ers a loss of \$1 (relative to the outside option value) in the afternoon but receives a better deal with three trips in the morning. Alternatively, he works only in the morning and obtains a total surplus of \$4. Therefore, Jack is better o working full-time. The platform earns \$6 by serving six passengers with a preferential algorithm versus \$4 by serving four passengers with a \fair" assignment. Therefore, the platform favors a preferential algorithm that compensates Jack in the morning for working in the afternoon.

Table 2: Jack's Choices under Di erent Algorithms

		AM	PM	payo
non-pref	part time	2	3	5 X
	full time	2	2	4
pref	part time	1	3	4
	full time	3	2	5 X

Notes: * outside option values.

While it is well-known that ride-hailing companies use dynamic pricing in rider fare that re ects demand and supply at di erent times, few papers study how the hourly work schedule a ects the wage rate. Our example highlights that the platform balances demand and supply through the cross-time elasticity of substitution in labor supply. Algorithms can set di erential wage rates based on the driver's overall work schedule. Thus, with a preferential algorithm, some drivers may prefer to work even in hours when outside options are more attractive, because they are rewarded in other hours. Most platforms apply surge pricing to balance demand and supply, which leverages real-time labor supply elasticity by increasing prices when demand exceeds supply (Castillo, 2020). The platform in our example can also increase supply by raising passenger fares in the afternoon. 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 demand is overly elastic and instead reward drivers when demand is less elastic. As a result, platforms relying on such algorithms profit from maximizing total transactions.

The richer model we develop in our paper builds on the intuition from this simple example. We endogenize drivers' dynamic labor supply and passenger demand by the hour on a typical day. Online Appendix C contains simulation results using a two-period version of the rich model. We find that the underlying outside option values and passenger demand elasticity determine the platform's preferred algorithm and the drivers' and passengers' gains/losses under a preferential algorithm. Such ambiguity motivates our quantitative exercise in the latter parts of our paper.

3 Industry Background and Data

We first describe the ride-hailing industry in the focal market. Anecdotal evidence suggests that ride-hailing platforms' algorithm rewards drivers with preferential order assignment. That is, drivers who work more total hours, preferably during incentivized hours, are prioritized in the assignment of orders (the so-called "high-performing" drivers). We confirm this in our interviews with drivers and software engineers of ride-hailing platforms. To rigorously study the wage differential between high-performing and low-performing drivers, we obtain 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. We also observe attributes of drivers such as gender and age. Section 3.2 describes the data set and provides summary statistics. Based on the anecdotal evidence and our survey results, we formally define high-performing and low-performing drivers in Section 3.3.

3.1 Industry Background

With the development of Asia's residential travel demand, the number of ride-hailing users in Asia grew to 800 million by the end of 2020.[3] Our paper focuses on one of the leading ride-hailing platforms in Asia,[4] which for confidential reasons, we refer to as Platform X. 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.[5] Platform X dominates the ride-hailing market and captures over a 90% share in the focal market on which we have

[3] Asia's consumers on the move: The future of mobility (McKinsey & Co., 2021).

[4] The leading ride-hailing platforms in Asia include Uber, Lyft, Didi, Grab, Gojek, Ola, among others.

[5] 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.

data. Below, we summarize how Platform X matches drivers and riders, how Platform X assigns orders, and what the fare schedules are. To further verify our understanding, we also hired a group of assistants to take a random set of trips using Platform X and conduct interviews with their drivers.

Platform X matches drivers and riders in three steps: First, riders request a trip through their phone app. The request includes the origin and destination of their routes and an estimated fare. The estimated fare is determined by the algorithm and based on the distance of the proposed trip, predicted tra c status, and time of day. Second, the platform distributes the request to a nearby driver. One feature of Platform X that di ers from Uber and Lyft in the U.S. is that drivers rarely decline requests unless under extreme circumstances, such as if the wait time for the rider is too long.[6] Third, upon receiving the request, the drivers drive to the speci ed origin to pick up their riders and deliver them to their destinations. The drivers cannot change the destination or distance of a trip and must follow the platform's guidance. According to our survey, most drivers strictly follow the route directed by the app. For each completed trip, drivers are paid a base fare plus a per-mile and per-minute rate according to the time of the day and distance of the hailed trip.

Regarding order assignment, Platform X usually distributes requests to drivers within three kilometers, but the radius may be larger when there are few available drivers nearby. Within the given radius, Platform X prioritizes speci c drivers based on their work schedules for order assignments. Anecdotes suggest that Platform X roughly categorizes drivers into two groups: (a) high-performing drivers, who work long hours and during speci c hours on the platform, and (b) low-performing drivers, whose work schedules are more casual. The platform's algorithm favors high-performing drivers by prioritizing order assignments for them. Our survey of drivers con rms such anecdotes. Casual drivers complain they \wait too long for orders" and \spend most of their time picking up riders." Committed drivers who usually work long hours on the platform are relatively satis ed with the status quo, \always receiving a new order immediately after nishing an order." Our survey also suggests that drivers know what the algorithm favors: i.e., those who work more total hours, and those who work more when there is a labor shortage (the so-called \incentivized hours" speci ed by the platform). Based on institutional knowledge and our survey results, we formally de ne high-performing and low-performing drivers in Section 3.3. We rigorously examine

[6] Technically speaking, drivers are allowed to cancel orders on Platform X. However, the process is complicated, and only a few drivers cancel orders. First, drivers cannot cancel orders directly on the app. They have to call customer service, wait for a representative to answer, explain why they have to cancel the order, and wait for the representative to cancel the order. In our data, we observe whether an order was canceled. If an order was canceled, we also observe whether the driver or the customer canceled the order. We utilize such information in ruling out the alternative hypothesis in our analysis.

the wage di erential between the two types of drivers and rule out alternative explanations other than a preferential algorithm in Section 4.

Regarding the fare schedules, drivers receive 79% of the rider fare, according to Platform X's annual report. The share is relatively constant according to the drivers we interviewed. In the city we study (as of 2018), Platform X fare schedules divide a work day 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). 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. All the drivers face the same fare schedules on Platform X. Thus, hourly wage di erentials across drivers mainly come from systematic di erences in order assignment.

3.2 Data

We obtain data from the Transportation Bureau of a major city in Asia. In these data, we observe all the completed transactions in December 2018. In each observation, we observe the departure, destination, and distance of a trip, the time spent picking up and transporting passengers, and the price paid by the driver. We also observe drivers' attributes such as age, gender, and birth location. Our detailed transaction-level data allows us to observe the detailed work schedules of the drivers and detailed information on the orders they received, allowing us to calculate drivers' hourly wage rates. Speci cally, our data has two advantages. First, the detailed driver work schedules allow us to identify whether certain types of work schedules are given higher wages than others. Second, the order details on origin, destination, wait time, pick-up time, and drive time allow us to evaluate the quantity and quality of orders received by di erent types of drivers and explore the source of the wage di erential. Our main analysis focuses only on Platform X. There are two reasons for this. First, Platform X dominates the market in the city we study,[7] accounting for over 90% of the market. Second, our data suggest that drivers rarely multi-home or switch between di erent platforms. Appendix E shows a detailed analysis regarding multi-homing. These two reasons suggest that competition between platforms is almost negligible in our city of study. Therefore, we focus only on Platform X in our main analysis.

Table 3 summarizes our data set. The unit of observation is at the driver-hour level.[8] A

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

[8] The unit of observation in our raw database is at the driver-rider-order level. Because the supply, demand, and fee schedules di er across weekdays and weekends, we focus on weekdays (21 days in total). Following

driver serves, on average, 1.9 orders per hour and earns 50 CCY. The number of orders varies from 1 to 3 between the 25^{th} and 75^{th} percentiles. 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.

Table 3: 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			

Our data has 40,104 unique drivers, among which 2.7% are female drivers, and 62.6% are non-local drivers. We define local drivers as drivers with local household registration permits.[9] Table 4 reports the driver characteristics. Drivers work a median of 13 days out of the 21 workdays. There is considerable heterogeneity across how many days each driver works. The number of days varies from 5 to 19 days between the 25^{th} and 75^{th} percentiles of drivers. The variation in the number of work hours per day is also substantial: the 25^{th} percentile driver works 4.8 hours compared to 10.5 hours from the 75^{th} percentile driver. Compared to Uber data from the US market, the summary statistics of 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 put in far more time (roughly 7.6 hours per day) than Uber drivers, who typically work approximately 3 hours per day. The preferential algorithm we describe in this study may be the cause of the large disparity.

3.3 High-Performing and Low-Performing Drivers

Both anecdotal evidence and our survey results show that the platform prioritizes high-performing drivers, who work long hours and during times of day with driver shortages, for order assignments. While we do not observe explicit driver performance labels, we construct

the literature, we conduct our main demand estimation and counterfactual analysis at the driver-hour level. Appendix D explains how we construct the driver-hour level data from the raw data.

[9] Household registration permits are issued by the government, and indicate the particular area a person is from, in which the registrant is entitled to benefits such as hospitals, schools, or land-purchasing rights.

Table 4: 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

these variables based on institutional knowledge. We then validate the clustering of drivers using evidence from our data and provide robustness checks for the clustering of drivers using machine learning algorithms.

First, we investigate which types of driver work schedules are more likely to be preferred by the algorithm, generating higher hourly wages. Based on our interviews, during our time of study mid-day and night hours (after 7 PM) were specified as incentivized hours. 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. Table 5 shows the results. Generally, drivers who work more, especially during incentivized hours, earn a higher hourly wage than other drivers. Column (2) of Table 5 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 8.7% 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 64% of the average hourly wage. The results are consistent with the anecdotal evidence that the platform prioritizes high-performing drivers, who work long hours and work more during incentivized hours, for order assignments.

We also conduct additional regression analyses that take a finer look at different time intervals and examine driver demographics that may have explanatory power over wage differentials. Appendix F shows the results. In summary, the results confirm our earlier finding that drivers' hourly wages are higher when they work more during incentivized hours (midday and at night). Moreover, upon controlling for the work schedule of drivers, there is little evidence of wage differentials based on driver demographics.

We formally define high-performing and low-performing drivers based on our survey and the suggestive evidence in Table 5. A driver is high-performing if he or she worked at least two consecutive hours during incentivized hours (midday or night) for at least 8 out

Table 5: 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 xed e ects, origin district xed e ects, and destination district xed e ects. Standard errors are in parentheses. *** p< 0.01.

of the 21 workdays, and is low-performing otherwise.[10] Then, we validate our de nition of high-performing and low-performing by checking the clustering of drivers. For each hour, a driver can choose whether to work or not. Therefore, the number of possible driver work schedules on any given day is 2^{24}. We implement machine learning algorithms to cluster drivers based on their hourly wages, work schedule, and other observed characteristics of drivers.[11] The result shows that there exist two groups of drivers, and the result is robust to various speci cations. The drivers with relatively higher hourly wages tend to work longer and more during incentivized hours. The ndings are consistent with our results in Table 5 and validate our de nition of high-performing and low-performing drivers.

Table 6 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-

[10] 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 de nitions. 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 xed 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.

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

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 (1.90 orders versus 1.76 orders) and earn more (50.4 versus 46.5 CCY per hour) compared to low-performing drivers. In Section 4, we rigorously examine the wage differential between high-performing and low-performing drivers, investigate the mechanism driving this wage differential, and rule out alternative explanations, including drivers strategically choosing orders, drivers having experience in choosing hot spots, and differences in driving speed.

Table 6: 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 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.

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 7 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.

Table 7: 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. *** $p < 0.01$

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 8 shows the results. Column (1) shows that conditional on working in the same hour, high-performing drivers receive more orders than low-performing drivers. On average, high-performing drivers receive 1.025 more orders or 7.1% more every hour. Second, orders assigned to high-performing drivers are 8.2% less likely to be canceled by riders (column 2).[12] 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).[13] More importantly, high-performing drivers spend 10.5% less time waiting for orders (column 5). This result is consistent with our argument in Section 3 that the algorithm prioritizes high-performing drivers for better order assignments.

Table 8: 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. *** $p < 0.01$

In summary, Table 8 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.

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

[12] 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.

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

schedules when assigning orders, some may argue that drivers make decisions endogenously, resulting in the observed wage di erence. For example, Cook, Diamond, Hall, List and Oyer (2021) nds 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 ndings, 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.[14] There are eight districts in the city we study. We rst examine where the high-performing and low-performing drivers work and whether they tend to pick up / drop o clients in di erent areas. Table 9 suggests no substantial di erence between the origin or destination districts where high-performing and low-performing drivers work.

Table 9: 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%

[14] For example, Haggag, McManus and Paci (2017) nds that New York taxi drivers accumulate neighborhood-speci c experience, which helps to nd riders.

To better control for location-fixed effects, we manually divide the eight districts into even finer 1km × 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-grid fixed effects, column (2) of Table 10 reports the result, which is almost identical to our main result in column (1).[15] 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-region 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 similar to our benchmark result in column (1). Thus, knowledge of hot spots and strategically choosing where to work is an unlikely explanation for the wage differential between high-performing and low-performing drivers.

Table 10: Wage Differentials with Finer Grids

Dependent Variables	Hourly Wage			
	(1)	(2)	(3)	(4)
High-Performing	3.850***	3.862***	3.693***	3.721***
	(0.0391)	(0.0385)	(0.0382)	(0.0375)
Constant	47.24***	46.51***	47.29***	46.64***
	(0.0701)	(0.0364)	(.0684)	(0.0355)
Controls:				
Day-Hour	Y	Y		
Day-Hour-15Minute			Y	Y
Origin/Destination	Y		Y	
1km × 1km Grid		Y		Y
Observations	4,182,318	4,182,318	4,182,318	4,182,318
R-squared	0.050	0.095	0.094	0.141

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

[15] Column (1) of Table 10 is identical to column (3) of Table 7, where we control for origin, destination, and day-hour fixed effects.

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 11 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. As explained in Section 3.1, 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 11 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,[16] 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,

[16] 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 $0.12 \times 2 = 0.24$ CCY. Therefore, this 0.5% faster-driving speed only converts into an extra 0.24 CCY per hour.

Table 11: 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 first estimate our model using simulated methods of moments and then conduct counterfactual experiments based on the estimated parameters.

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. [17] 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.

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

5.1 Drivers' Dynamic Labor Supply

In the first stage, a driver chooses 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 3.3, drivers need to work longer hours during incentivized hours to be a high-performing type. More specifically, our model assumes that 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,

[17] Because we have a short panel, we leave day-to-day dynamic labor supply for future research. Moreover, working long hours and consecutive incentivized hours explain the preferential algorithm in our data. Dynamic labor supply under the long-hours constraint is a much more complicated problem than the consecutive-hours constraint. Fortunately, the two criteria are highly correlated, so we approximate the algorithm by solely considering the rewarding of those who consecutively work incentivized hours.

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.[18] Work status is summarized by different work schedules, $L \in \{0\}$ and $H \in \{1, \dots, 16\}$. 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.[19] 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 $N^L = N_0$.

In the second stage, drivers 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, sequence of hourly wages W, and reservation values 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 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:

$$\begin{aligned} U_{1t} &= \underbrace{W_t}_{\text{preferential wage rate}} + \epsilon_{1t}; \\ U_{0t} &= \underbrace{O_t}_{\text{outside option value}} + \epsilon_{0t}; \end{aligned} \tag{1}$$

[18] 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.

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

where O_t represents the reservation value from working on something else, and $_t$ represents the error term that is Type-I extreme value distributed. There is a fixed warm-up cost > 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. For each set of parameters $(O; \; ; \;)$ and sequence of wages $W \; \{W^H; W^L\}$, we can solve each driver's problem and obtain type-specific values.

We solve the dynamic discrete choice (DDC) problems through backward induction. Appendix A contains the derivation details. The solutions generate conditional choice probabilities and the number of drivers working each hour by work schedule. Individual driver choices, in turn, generate the aggregate labor supply for each hour by driver type:

$$N_t^H = \sum_{j=1}^{16} N_j \quad \Pr(\text{work in hour } t \,|\, \text{work schedule } j)$$
$$N_t^L = N_0 \quad \Pr(\text{work in hour } t \,|\, \text{work schedule } 0;)$$

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

$$N_t^H = N_t^H(W^H; \;) = N_t^H(P; s; \;);$$
$$N_t^L = N_t^L(W^L; \;) = N_t^L(P; s; \;):$$

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:

$$Q_t = D_t(P_t) = \;_t P_t \; ;$$

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

The platform takes demand shifter $_t$ and demand elasticity 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 $(P; s)$ maximizes its own payoff:

$$
\begin{aligned}
\max_{(P;s)} \quad & (1-\tau)\sum_t P_t D_t(P_t) \\
\text{s.t.} \quad & D_t(P_t)s_t \le \alpha_t^H N_t^H(P;s;\tau) \\
& D_t(P_t)(1-s_t) \le \alpha_t^L N_t^L(P;s;\tau):
\end{aligned} \tag{2}
$$

$D_t(P_t)$ is the demand for rides measured in earning hours, and N_t represents the total number of working hours (active app hours) provided by the drivers. We have α_t as the technological constraint restricting the relationship between working hours and earning hours, where $\alpha_t \in [0;1]$. For example, $\alpha_t = 0.5$ means that for every 15 minutes driving with a rider, a typical driver spends another 15 minutes on pick up, payment, etc. If $\alpha_t = 1$, there is no time spent on pick up.[20] 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 τ equal to 20%.[21]

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

$$
\begin{aligned}
W_t^H &= \gamma P_t D_t(P_t) s_t \frac{1}{N_t^H}; \\
W_t^L &= \gamma P_t D_t(P_t)(1-s_t) \frac{1}{N_t^L};
\end{aligned} \tag{3}
$$

where γ 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 houh. 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 parameters are estimated through:

$$
\log Q_t = \log \theta_h - \beta \log P_t + e_h: \tag{4}
$$

[20] 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.

[21] 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 $\tau = 0.2$ in our empirical analysis.

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 ϵ_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 12: Demand Estimation

Dependent Variables	ln(Service Hours)			
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	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	N	N	Y	Y
Day of Week FE	N	N	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 12 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

Next, we estimate the structural parameters: $(\{O_t\};\ ;\ )$. $\{O_t\}$ is the reservation value at each time t, is the warm-up cost of starting to work, and is the normalization term of EVT1 errors (the scale parameter). 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 at each time t. Given the utility of working for each hour in equation 1, the conditional probability of working for low-performing drivers is

$$\begin{aligned} P_L(a_t = 1 | a_{t\ 1} = 1) &= \frac{\exp((W_t^L + \ EV^L_{1t+1})/\ )}{\exp((W_t^L + \ EV^L_{1t+1})/\ ) + \exp((O_t + \ EV^L_{0t+1})/\ )}; \\ P_L(a_t = 1 | a_{t\ 1} = 0) &= \frac{\exp((W_t^L \quad {}_t + \ EV^L_{1t+1})/\ )}{\exp((W_t^L \quad {}_t + \ EV^L_{1t+1})/\ ) + \exp((O_t + \ EV^L_{0t+1})/\ )}; \end{aligned} \tag{5}$$

where $t \in [2; T\ \ 1]$. Throughout our model, EV's subscript 1 represents $a_{t\ 1} = 1$. In this case, EV^L_{1t} represents the expected value of low-performing drivers at time t if $a_{t\ 1} = 1$. 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

$$\begin{aligned} P_H(a_t = 1 | a_{t\ 1} = 0) &= \sum_{j=1}^{16} \hat{P}_j \quad P_j(a_t = 1 | a_{t\ 1} = 0); \\ P_H(a_t = 1 | a_{t\ 1} = 1) &= \sum_{j=1}^{16} \hat{P}_j \quad P_j(a_t = 1 | a_{t\ 1} = 1); \end{aligned} \tag{6}$$

where $\hat{P}_j$ is the probability of choosing schedule j within high-performing drivers. Therefore, equations 5 and 6 show the model-predicted CCPs as a function of observed wage sequence $\{W^H; W^L\}$ and parameters . In Appendix A.3, we show the detailed derivation of $P\ (a_t = 1 | a_{t\ 1} = 0)$ and $P\ (a_t = 1 | a_{t\ 1} = 1)$ for $\ \in \{L; H\}$ and $t \in [1; 24]$.

Then, from the data, we obtain the observed CCPs of high-performing and low-performing drivers at each time t. Figure 1 shows the CCPs obtained from the data. First, we can see that the conditional probability of working when the driver has already started working ($a_{t\ 1} = 1$) is much higher than the conditional probability of working when the driver was not working ($a_{t\ 1} = 0$) for both types of drivers. This indicates that there exists a high warm-up cost. Second, the observed conditional probability of working for high-performing drivers is higher than for low-performing drivers at all times of the day. However, the difference is smaller at night between 11 PM to 6 AM the next day. Third, the conditional probability of working is higher during morning hours from 7 AM–10 AM and afternoon hours from 4 PM–7 PM. It indicates that drivers' reservation values vary across different times of the day.

Figure 1: Conditional Probability of Working (from data)

The estimation of the dynamic parameters θ_0 is implemented according to the following procedures. First, denote the actual CCPs obtained from the data as $P^d(\cdot)$, which is a 48-by-1 vector. Second, for a given set of parameters θ, the model-simulated CCPs are $P^S(\theta)$. The MSM estimate $\hat{\theta}$ minimizes the weighted distance between the data moments and the simulated moments:

$$L(\theta) = \min_{\theta} \; [P^d - P^S(\theta)]' W [P^d - P^S(\theta)];$$

where W is a positive definite matrix. Figure B.1 shows the model's goodness of fit. Overall, the simulated values fit the observed CCPs well.

Figure 2 shows the estimated reservation values for a driver. The average estimated reservation value is 49 CCY. 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. 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 2: Estimated Reservation Values

6.3 Unobserved Heterogeneity

In our benchmark model, we assume that reservation values $\{O_t\}$ vary solely across time and not across different groups of drivers. However, there could be unobserved heterogeneity in reservation values for different groups of drivers that affects drivers' dynamic labor supply decisions. Therefore, we aim to capture driver heterogeneity by estimating their unobserved heterogeneity. After introducing unobserved heterogeneity the utility of working and not working can now be specified, at each hour t, as

$$U_{1t} = W_t + \quad {}_{1t};$$
$$U_{0t} = O_t + \ {}_{s;t} + \quad {}_{0t};$$

where ${}_{s;t}$ is the fare-schedule-specific unobserved heterogeneity. For example, driver group 0 is our benchmark case. Driver group 1 will have an unobserved heterogeneity term ${}_1$ for 7 AM to 10 AM. Driver group 2 will have an unobserved heterogeneity term ${}_2$ for 10 AM to 4 PM. We allow for seven types of unobserved heterogeneity based on Platform X's fare schedules (details of the fare schedules are explained in Section 3.1). We follow Arcidiacono and Miller (2011) in estimating the unobserved heterogeneity. In Appendix A.4, we explain the details of solving the model with unobserved heterogeneity and the estimation procedure.

Table 13 shows the 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 13 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 13: 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. Driver groups 2 and 4 have low reservation values at mid-day and early-night, respectively. Other driver groups have similar estimated reservation values. Table 13 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). Next, to better understand the estimated driver groups, we map the observed driver characteristics to the driver groups.

Figure 3: Estimated Reservation Values with Unobserved Driver Heterogeneity

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.[22] 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 drivers are grouped into the Rest group.

Table 14 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. Mapping the observed driver characteristics to the estimation results of unobserved heterogeneity, we can see that female and older drivers are more likely to be in driver group 2. Young, local, and male drivers are more likely to be in driver groups other than 2 and 4.

Table 14: 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

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

[22] 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.

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 (demand elasticity) and the warm-up cost parameter, 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

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

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

$$U_{1t} = \underbrace{\widetilde{W}_t}_{\substack{\text{non-preferential}\\ \text{wage rate}}} + \varepsilon_{1t};$$

$$U_{0t} = \underbrace{O_t}_{\text{outside option value}} + \varepsilon_{0t};$$

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.[23] 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

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

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.

(a) Labor Shortage

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

Figure 4: Illustration of Leveraging Cross-time Elasticity

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

$$E_t(h) = \frac{\left(N_t(\tilde{W}^H; \tilde{W}^L) - N_t(W^H; W^L)\right) / N_t(W^H; W^L)}{(\tilde{W}_h^H - W_h^H)/W_h^H};$$

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 di erent hours of the day. Given that multiple-hour labor supply responds to the wage di erential at one particular hour, the platform can strategically choose when to provide high incentive wages. In Appendix H, we replicate this exercise by changing the treatment hour from 7 AM to 6 PM.

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

Next, we show the welfare e ects of eliminating the preferential algorithm. We study the welfare e ects in both the short run and the long run. In the long run, the platform will re-optimize the hourly ride fares $\tilde{P}$ to maximize its payo :[24]

$$\begin{aligned} &\max_{\tilde{P}} \ (1 \quad) \sum_t P_t D_t(P_t) \\ &\text{s.t.} \ D_t(P_t) \quad \tilde{e}_t N_t(W_t; \ ) \end{aligned} \tag{7}$$

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 $\sum_t \int_{P_t}^{1} {}_t x \ dx$ and the driver surplus of each schedule j as

$$EV_0^j = \Big[\ln \ \exp((\tilde{W}_1 \quad + \ EV_{12})/\ ) + \exp((O_1 + \ EV_{02})/\ ) \ + \quad \Big];$$

[24] Note that the two feasibility constraints in equation 2 become one because all drivers have the same likelihood of receiving a task, and $\tilde{e}_t$ is the technology restriction without algorithmic preferential wage-setting. Under "fair" pay, there is only one group, so $s = 1$.

where EV_0^j represents the expected value choosing each work schedule type.[25] Table 15 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" 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 0.69% increase in surplus. In aggregate, the total surplus will decrease by 7.16% if we eliminate the preferential algorithm.

Table 15: 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

[25] Note that consumer surplus $\sum_t \int_{P_t}^{\infty} \alpha_t x^{-\epsilon} dx = \sum_t \frac{\alpha_t}{\epsilon - 1}(P_t)^{1-\epsilon} = \frac{1}{(\epsilon-1)(1-\eta)}$ platform revenue. In the short term, the total number of riders served equals to $\min\{D_t(P_t); e_t N_t(W_t; \cdot)\}$.

extensive margin, the probability of being high-performing decreases by 14.8 percentage points in the short term and decreases by 9.8 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 6.3. Table 16 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.

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.

Table 16: 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.

7.2 Factors Determining Preferential Algorithm E ectiveness

To further investigate what factors determine the e ectiveness of the preferential algorithm, we conduct counterfactuals by alternating key structural parameters. Motivated by our two-period model in Appendix C, we focus on the demand elasticity and warm-up cost . Table 17 shows the results when we alter the value of demand elasticity. When demand is more elastic, the platform bene ts more from utilizing the cross-time di erence in elasticity by implementing the preferential algorithm. Therefore, in column (1) of Table 17, 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 su er less from the preferential algorithm if demand elasticity increases. Total driver surplus will decrease by 3.02% when demand is more elastic, compared to a decrease of 4.09% 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 17 con rms 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 9.08% to 0.17%.

Table 17: Varying the Value of Demand Elasticity

Demand Elasticity	Changes in (With - Without)			
	Platform Revenue/ Consumer Surplus	Driver Surplus	Driver Surplus (Low-performing)	Average Wage
Benchmark	1.44%	-0.49%	-0.98%	-7.26%
1:1	2.13%	-0.47%	-0.52%	-6.55%
1:2	2.60%	-0.40%	-0.29%	-5.78%
1:3	2.89%	-0.32%	-0.17%	-5.03%

Next, we examine the e ect of the warm-up cost . Table 18 shows the results when we vary the value of the warm-up cost . 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 pro table 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 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 17 con rms 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.[26]

Table 18: Varying the Value of Warm-up Cost

Warm-up Cost	Changes in (With - Without)			
	Platform Revenue/ Consumer Surplus	Driver Surplus	Driver Surplus (Low-performing)	Consumers Served
Benchmark	1.44%	-0.49%	-0.98%	9.55%
1:1	1.45%	-0.49%	-0.93%	9.64%
1:2	1.46%	-0.49%	-0.86%	9.71%
1:3	1.47%	-0.48%	-0.79%	9.76%

[26] In the second case, when we alter the value of the warm-up cost, showing the change in average wage will not directly reveal how driver surplus changes, because driver utility is a ected by both the warm-up cost and average wage. Instead, when demand elasticity is xed in the second case, the surplus of low-performing drivers will monotonically increase with respect to the number of riders served. Similarly, in the rst case, when we alter the value of demand elasticity , 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 rst case, when the warm-up cost is xed, the surplus of low-performing drivers will monotonically increase with respect to the average wage rate. This is why we report di erent variables in the last column of Tables 17 and 18.

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.

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%, and the total surplus will decrease by :716% in the short term if we eliminate the preferential algorithm. The probability of drivers being high-performing will decrease by 1418% without a preferential algorithm. For the switchers, driver surplus will increase by :531%. 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 Drivers' Finite-Horizon Dynamic Problem

This appendix describes in detail drivers' nite-horizon dynamic choices and our CCP estimator. For each hour t, the utility of working and not working are speci ed as

$$U_{1t} = W_t + {}_{1t};$$
$$U_{0t} = O_t + {}_{0t}:$$

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

A.1 Low-Performing Drivers

For the nal period, $t = T$,

$$V_T^L = \begin{cases} W_T^L + {}_{1T} & \text{if } a_T = 1 \ \& \ a_{T\ 1} = 1; \\ W_T^L \quad + {}_{1T} & \text{if } a_T = 1 \ \& \ a_{T\ 1} = 0; \\ O_T + {}_{0T} & \text{if } a_T = 0: \end{cases}$$

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

$$EV_{1T}^L = \left[\ln \ \exp(W_T^L = \ ) + \exp(O_T = \ ) \ + \ \right];$$
$$EV_{0T}^L = \left[\ln \ \exp((W_T^L \quad) = \ ) + \exp(O_T = \ ) \ + \ \right]:$$

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 $t \ 2 \ [T \quad 1; 2]$,

$$V_t^L = \begin{cases} W_t^L + {}_{1t} + \ EV_{1t+1}^L & \text{if } a_t = 1 \ \& \ a_{t\ 1} = 1; \\ W_t^L \quad + {}_{1t} + \ EV_{1t+1}^L & \text{if } a_t = 1 \ \& \ a_{t\ 1} = 0; \\ O_t + {}_{0t} + \ EV_{0t+1}^L & \text{if } a_t = 0: \end{cases}$$

So, the expected utility of period t is given by

$$EV_{1t}^L = \left[\ln \ \exp((W_t^L + \ EV_{1t+1}^L) = \ ) + \exp((O_t + \ EV_{0t+1}^L) = \ ) \ + \ \right];$$
$$EV_{0t}^L = \left[\ln \ \exp((W_t^L \quad + \ EV_{1t+1}^L) = \ ) + \exp((O_t + \ EV_{0t+1}^L) = \ ) \ + \ \right]:$$

For the first period, $t = 1$,

$$V_1^L = \begin{cases} W_1^L \quad + \quad {}_{11} + \; EV_{12}^L & \text{if } a_1 = 1; \\ O_1 + \quad {}_{01} + \; EV_{02}^L & \text{if } a_1 = 0: \end{cases}$$

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

$$EV^L = \left[\ln \; \exp((W_1^L \quad + \; EV_{12}^L)= \;) + \exp((O_1 + \; EV_{02}^L)= \;) \; + \quad \right]: \qquad \text{(A.1)}$$

A.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 $j \in \{1; \quad ; 16\}$ with committed working hours $[T_0; T_0 + 1]$:

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

$$V_T^j = \begin{cases} W_T^H + \quad {}_{1T} & \text{if } a_T = 1 \;\&\; a_{T \quad 1} = 1; \\ W_T^H \quad + \quad {}_{1T} & \text{if } a_T = 1 \;\&\; a_{T \quad 1} = 0; \\ O_T + \quad {}_{0T} & \text{if } a_T = 0: \end{cases}$$

The expected utility of period T is given by:

$$EV_{1T}^j = \left[\ln \; \exp(W_T^H = \;) + \exp(O_T = \;) \; + \quad \right];$$
$$EV_{0T}^j = \left[\ln \; \exp((W_T^H \quad)= \;) + \exp(O_T = \;) \; + \quad \right]:$$

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

$$V_t^j = \begin{cases} W_t^H + \quad {}_{1t} + \; EV_{1t+1}^j & \text{if } a_t = 1 \;\&\; a_{t \quad 1} = 1; \\ W_t^H \quad + \quad {}_{1t} + \; EV_{1t+1}^j & \text{if } a_t = 1 \;\&\; a_{t \quad 1} = 0; \\ O_t + \quad {}_{0t} + \; EV_{0t+1}^j & \text{if } a_t = 0: \end{cases}$$

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

$$EV_{1t}^j = \left[\ln \; \exp((W_t^H + \; EV_{1t+1}^j)= \;) + \exp((O_t + \; EV_{0t+1}^j)= \;) \; + \quad \right];$$
$$EV_{0t}^j = \left[\ln \; \exp((W_t^H \quad + \; EV_{1t+1}^j)= \;) + \exp((O_t + \; EV_{0t+1}^j)= \;) \; + \quad \right]:$$

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:

$$V^j_{T_0+2} = \begin{cases} W^H_{T_0+2} + \quad {}_{1T_0+2} + \ EV^{\,j}_{1T_0+3} & \text{if } a_{T_0+2} = 1; \\ O_{T_0+2} + \quad {}_{0T_0+2} + \ EV^{\,j}_{0T_0+3} & \text{if } a_{T_0+2} = 0: \end{cases}$$

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

$$EV^j_{1T_0+1} = W^H_{T_0+1} + \ EV^{\,j}_{1T_0+2} + \quad :$$

At period T_0, the expected value is

$$\begin{aligned} EV^j_{1T_0} &= W^H_{T_0} + \ EV^{\,j}_{1T_0+1} + \quad ; \\ EV^j_{0T_0} &= W^H_{T_0} \quad + \ EV^{\,j}_{1T_0+1} + \quad : \end{aligned}$$

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

$$\begin{aligned} EV^j_{1t} &= \left[\ln \ \exp((W^H_t + \ EV^{\,j}_{1t+1})= \ ) + \exp((O_t + \ EV^{\,j}_{0t+1})= \ ) \ + \quad \right]; \\ EV^j_{0t} &= \left[\ln \ \exp((W^H_t \quad + \ EV^{\,j}_{1t+1})= \ ) + \exp((O_t + \ EV^{\,j}_{0t+1})= \ ) \ + \quad \right]: \end{aligned}$$

For period 1,

$$V^j_1 = \begin{cases} W^H_1 \quad + \quad {}_{11} + \ EV^{\,j}_{12} & \text{if } a_1 = 1; \\ O_1 + \quad {}_{01} + \ EV^{\,j}_{02} & \text{if } a_1 = 0: \end{cases}$$

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

$$EV^{\,j} = \left[\ln \ \exp((W^H_1 \quad + \ EV^{\,j}_{12})= \ ) + \exp((O_1 + \ EV^{\,j}_{02})= \ ) \ + \quad \right]: \qquad (A.2)$$

A.3 Estimation

We now describe how we adapt the CCP estimator to our setting.

A.3.1 Low-performing Drivers

For the nal period T, the conditional probability of working is

$$P_L(a_T = 1 j a_{T\ \ 1} = 1) = \frac{\exp(W_t^L = \ )}{\exp(W_t^L = \ ) + \exp(\ O_T^L = \ )};$$

$$P_L(a_T = 1 j a_{T\ \ 1} = 0) = \frac{\exp((W_t^L \quad _T) = \ )}{\exp((W_t^L \quad _T) = \ ) + \exp(\ O_T^L = \ )}:$$

For any t 2 [2; T 1],

$$P_L(a_t = 1 j a_{t\ \ 1} = 1) = \frac{\exp((W_t^L + \ EV_{1t+1}^{\ L}) = \ )}{\exp((W_t^L + \ EV_{1t+1}^{\ L}) = \ ) + \exp((\ O_t^L + \ EV_{0t+1}^{\ L}) = \ )};$$

$$P_L(a_t = 1 j a_{t\ \ 1} = 0) = \frac{\exp((W_t^L \quad _t + \ EV_{1t+1}^{\ L}) = \ )}{\exp((W_t^L \quad _t + \ EV_{1t+1}^{\ L}) = \ ) + \exp((\ O_t^L + \ EV_{0t+1}^{\ L}) = \ )}:$$

For t = 1,

$$P_L(a_1 = 1) = \frac{\exp((W_1^L \quad _1 + \ EV_{12}^{\ L}) = \ )}{\exp((W_1^L \quad _1 + \ EV_{12}^{\ L}) = \ ) + \exp((\ O_1^L + \ EV_{02}^{\ L}) = \ )}: \qquad (A.3)$$

A.3.2 High-performing Drivers

For any schedule j 2 f 1; ; 16g, the conditional probability of working in the nal period T is

$$P_j(a_T = 1 j a_{T\ \ 1} = 1) = \frac{\exp(W_t^H = \ )}{\exp(W_t^H = \ ) + \exp(\ O_T = \ )};$$

$$P_j(a_T = 1 j a_{T\ \ 1} = 0) = \frac{\exp((W_t^H \quad _T) = \ )}{\exp((W_t^H \quad _T) = \ ) + \exp(\ O_T = \ )}:$$

For any t 2 [T_0 + 3; T 1], we have

$$P_j(a_t = 1 j a_{t\ \ 1} = 1) = \frac{\exp((W_t^H + \ EV_{1t+1}^{\ j}) = \ )}{\exp((W_t^H + \ EV_{1t+1}^{\ j}) = \ ) + \exp((\ O_t + \ EV_{0t+1}^{\ j}) = \ )};$$

$$P_j(a_t = 1 j a_{t\ \ 1} = 0) = \frac{\exp((W_t^H \quad _t + \ EV_{1t+1}^{\ j}) = \ )}{\exp((W_t^H \quad _t + \ EV_{1t+1}^{\ j}) = \ ) + \exp((\ O_t + \ EV_{0t+1}^{\ j}) = \ )}:$$

At $t = T_0 + 2$, we have

$$P_j(a_t = 1 | a_{t-1} = 1) = \frac{\exp((W_t^H + EV^j_{1t+1})/)}{\exp((W_t^H + EV^j_{1t+1})/) + \exp((O_t + EV^j_{0t+1})/)}.$$

At $t = T_0 + 1$, we have

$$P_j(a_t = 1 | a_{t-1} = 1) = 1.$$

At $t = T_0$, we have

$$P_j(a_t = 1 | a_{t-1} = 1) = 1;$$
$$P_j(a_t = 1 | a_{t-1} = 0) = 1.$$

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

$$P_j(a_t = 1 | a_{t-1} = 1) = \frac{\exp((W_t^H + EV^j_{1t+1})/)}{\exp((W_t^H + EV^j_{1t+1})/) + \exp((O_t + EV^j_{0t+1})/)};$$
$$P_j(a_t = 1 | a_{t-1} = 0) = \frac{\exp((W_t^H - {}_t + EV^j_{1t+1})/)}{\exp((W_t^H - {}_t + EV^j_{1t+1})/) + \exp((O_t + EV^j_{0t+1})/)}.$$

At $t = 1$, we have

$$P_j(a_1 = 1) = \frac{\exp((W_1^H - {}_1 + EV^j_{12})/)}{\exp((W_1^H - {}_1 + EV^j_{12})/) + \exp((O_1 + EV^j_{02})/)}.$$

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

$$P_H(a_t = 1 | a_{t-1} = 0) = \sum_s \tilde{P}_j \, P_j(a_t = 1 | a_{t-1} = 0);$$
$$P_H(a_t = 1 | a_{t-1} = 1) = \sum_s \tilde{P}_j \, P_j(a_t = 1 | a_{t-1} = 1);$$

where $\tilde{P}_j$ is the probability of choosing each high-performing schedule.

A.4 Unobserved Heterogeneity

For each hour t, the utility of working and not working are speci ed as

$$U_{1t} = W_t + \quad {}_{1t};$$
$$U_{0t} = O_t + \quad {}_{s;t} + \quad {}_{0t}:$$

A.4.1 Low-Performing Drivers

Given the value function for each period t, we derive the CCP representation of the hourly labor supply decision.

For the nal period T,

$$V_T^L = \begin{cases} W_T^L + \quad {}_{1T} & \text{if } a_T = 1 \;\&\; a_{T\ 1} = 1; \\ W_T^L \quad + \quad {}_{1T} & \text{if } a_T = 1 \;\&\; a_{T\ 1} = 0; \\ O_T + \quad {}_{s;T} + \quad {}_{0T} & \text{if } a_T = 0: \end{cases}$$

Therefore, we have

$$v_{1T}^L \quad v_{0T}^L = W_T^L \quad 1(a_{T\ 1} = 0) \quad O_T \quad {}_{s;T};$$

where v_{1T}^L is the conditional expected future utility if $a_T = 1$.

At any time t 2 [T 1; 2],

$$V_t^L = \begin{cases} W_t^L + \quad {}_{1t} + \ EV_{1t+1}^L & \text{if } a_t = 1 \;\&\; a_{t\ 1} = 1; \\ W_t^L \quad + \quad {}_{1t} + \ EV_{1t+1}^L & \text{if } a_t = 1 \;\&\; a_{t\ 1} = 0; \\ O_t + \quad {}_{s;t} + \quad {}_{0t} + \ EV_{0t+1}^L & \text{if } a_t = 0: \end{cases}$$

Then, we derive the CCP representation of the hourly labor supply decision:

$$\begin{aligned} v_{1t}^L = W_t^L & \quad 1(a_{t\ 1} = 0) \\ & + \quad \ln \left[\exp((W_{t+1}^L + \ EV_{1t+2}^L)= \ ) + \exp((O_{t+1} + \quad {}_{s;t+1} + \ EV_{0t+2}^L)= \ ) \right] + \\ = W_t^L & \quad 1(a_{t\ 1} = 0) + \quad \ln \quad \exp((O_{t+1} + \quad {}_{s;t+1} + \ EV_{0t+2}^L)= \ ) \\ & 1 + \exp((W_{t+1}^L + \ EV_{1t+2}^L)= \quad (O_{t+1} + \quad {}_{s;t+1} + \ EV_{0t+2}^L)= \ ) \quad + \end{aligned}$$

$$= W_t^L \quad 1(a_{t \; 1} = 0) + \quad (O_{t+1} + \quad {}_{s;t+1} + \; EV^L_{0t+2})= \qquad \ln P_L(a_{t+1} = 0 | a_t = 1; s) + \quad :$$

Applying the same logic to the conditional value function for not working yields

$$v^L_{0t} = O_t + \quad {}_{s;t} + \quad \ln \Big[\exp((W^L_{t+1} \quad + \; EV^L_{1t+2})= \;) + \exp((\,O_{t+1} + \quad {}_{s;t+1} + \; EV^L_{0t+2})= \;) \Big] +$$

$$= O_t + \quad {}_{s;t} + \quad \ln \quad \exp((O_{t+1} + \quad {}_{s;t+1} + \; EV^L_{0t+2})= \;)$$

$$1 + \exp((W^L_{t+1} \quad + \; EV^L_{1t+2})= \quad (O_{t+1} + \quad {}_{s;t+1} + \; EV^L_{0t+2})= \;) \quad +$$

$$= O_t + \quad {}_{s;t} + \quad (O_{t+1} + \quad {}_{s;t+1} + \; EV^L_{0t+2})= \qquad \ln P_L(a_{t+1} = 0 | a_t = 0; s) + \quad :$$

Therefore, the di erence between the two conditional value functions is calculated as

$$v^L_{1t} \quad v^L_{0t} = W^L_t \qquad 1(a_{t \; 1} = 0) \quad O_t \qquad {}_{s;t}$$
$$+ \quad \ln P_L(a_{t+1} = 0 | a_t = 0; s) \qquad \ln P_L(a_{t+1} = 0 | a_t = 1; s):$$

For the rst period, $t = 1$,

$$v^L_{11} \quad v^L_{01} = W^L_1 \qquad O_1 \qquad {}_{s;1}$$
$$+ \quad \ln P_L(a_2 = 0 | a_1 = 0; s) \qquad \ln P_L(a_2 = 0 | a_1 = 1; s):$$

A.4.2 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 2 f 1; ; 16g with committed working hours $[T_0; T_0 + 1]$:

For the last period T,

$$v^H_{1T} \quad v^H_{0T} = W^H_T \qquad 1(a_{T \; 1} = 0) \quad O_T \qquad {}_{s;T}:$$

At t 2 $[2; T_0 \quad 1] [\; [T_0 + 3; T \quad 1]$,

$$v^H_{1t} \quad v^H_{0t} = W^H_t \qquad 1(a_{t \; 1} = 0) \quad O_t \qquad {}_{s;t}$$
$$+ \quad \ln P_j(a_{t+1} = 0 | a_t = 0; s) \qquad \ln P_j(a_{t+1} = 0 | a_t = 1; s):$$

At $t = T_0 + 2$,

$$\begin{aligned} v^H_{1t} \quad v^H_{0t} = W^H_t \quad O_t \quad {}_{s;t} & \\ + \quad \ln P_j(a_{t+1} = 0 | a_t = 0; s) \quad \ln P_j(a_{t+1} = 0 | a_t = 1; s): & \end{aligned}$$

For the first period, $t = 1$,

$$\begin{aligned} v^H_{1t} \quad v^H_{0t} = W^H_t \qquad O_t \quad {}_{s;t} & \\ + \quad \ln P_j(a_{t+1} = 0 | a_t = 0; s) \quad \ln P_j(a_{t+1} = 0 | a_t = 1; s): & \end{aligned}$$

Notice that when $t = T_0$ and $t = T_0 + 1$, the probability of working is 1 for high-performing drivers.

A.5 Estimation with Unobserved Heterogeneity

The model is estimated by maximizing the log likelihood of the finite mixture model:

$$f\hat{;}\ \hat{}g = \arg\max_{;} \sum_{i=1}^{N} \ln \left[\sum_{s} {}_s \prod_{t=1}^{24} l(a_{it} | s; \hat{p}; a_{it\ 1}; \ ) \right];$$

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

We can express the likelihood as follows:

$$l(a_{it} | s; \hat{p}; a_{it\ 1}; \ ) = \frac{a_{it} \exp((v_{1t} \quad v_{0t}) = \ ) + (1 \quad a_{it})}{1 + \exp((v_{1t} \quad v_{0t}) = \ )}:$$

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

$$q^{(m+1)}_{ns} = \frac{{}^{(m)}_{s} \prod_{t=1}^{24} l(a_{it} | s; \hat{p}; a_{it\ 1}; \ )}{\sum_{s^0} {}^{(m)}_{s^0} \prod_{t=1}^{24} l(a_{it} | s^0; \hat{p}; a_{it\ 1}; \ )}:$$

Then, use $q^{(m+1)}_{ns}$ to compute ${}^{(m+1)}_{s}$ according to

$${}^{(m+1)}_{s} = \frac{1}{N} \sum_{n=1}^{N} q^{(m+1)}_{ns}:$$

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 ${}^{(m+1)}$ from

$${}^{(m+1)} = \arg\max \sum_{i=1}^{N} \sum_{s} \sum_{t=1}^{24} q_{ns}^{(m+1)} \ln[l(a_{it}|s; \hat{p}; a_{it\ 1};\ )]:$$

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

$$q_{nsj}^{(m+1)} = \frac{{}_{sj}^{(m)} \prod_{t=1}^{24} l(a_{it}|s; \hat{p}; a_{it\ 1};\ ; j)}{\sum_{s'} \sum_{j'} {}_{s'j'}^{(m)} \prod_{t=1}^{24} l(a_{it}|s'; \hat{p}; a_{it\ 1};\ ; j)}:$$

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

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

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 ${}^{(m+1)}$ from

$${}^{(m+1)} = \arg\max \sum_{i=1}^{N} \sum_{s} \sum_{j} \sum_{t=1}^{24} q_{nsj}^{(m+1)} \ln[l(a_{it}|s; \hat{p}; a_{it\ 1};\ ; j)]:$$

B Model Validation

Figure B.1 shows the model's goodness of fit. First, for both high-performing and low-performing drivers, the simulated CCPs fit the observed CCPs well when $a_{t-1} = 1$. The simulated CCPs fit well for low-performing drivers when $a_{t-1} = 0$. However, the fit of high-performing drivers at $a_{t-1} = 0$ is a little off. This might be because the observed CCPs of high-performing drivers and low-performing drivers are quite different when $a_{t-1} = 0$. Our model is not able to capture this difference, because we assume that the reservation values are the same among low-performing and high-performing drivers in our benchmark model.

(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 B.1: Model Goodness of Fit

Note: Figure B.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

C A Two-Period Example with Logit Demand

First, we will provide a theoretical framework to explain why platforms have incentive to use preferential algorithms. The intuition is that these sorts of platforms face low driver supply during certain hours and normally would have to provide high payments during that period to incentivize participation. As platforms would like to avoid paying these very high incentive wages, one solution has been to reward drivers who do participate with higher quality orders (through the so-called \preferential algorithm") during regular hours.

To formally elaborate on this intuition, we propose a two-period model. In each period, there is a demand for rides, represented by

$$D_t(P_t) = \ _tP_t^{\ \ t}:$$

There is a mass of M drivers, who decide whether to work or not in each time period. If a driver works at time t, she earns wage W_t. If not, she receives reservation value O_t. The platform charges commission fee 1 , and hence the wage in each time period is P_t.

$$u_{1t} = W_t + \ _{1t} = \ P_t + \ _{1t};$$
$$u_{0t} = O_t + \ _{0t}:$$

The platform chooses ride fares in both periods to maximize pro t.

We study two scenarios. In scenario A, there is no preferential algorithm, and drivers enjoy full exibility in choosing whether to work for each time period. In scenario B, the preferential algorithm prioritizes high-performing drivers who work both periods, and low-performing drivers who only work one period earn 0.[27]

[27] In the motivational example, we assume that the preferential algorithm assigns all orders to high-performing drivers, and hence low-performing drivers earn 0 pro t. Assigning all orders to high-performing drivers is an extreme case and may not be optimal. Here, we just want to highlight the main trade-o in this extreme case. In our full model in Section 5, we allow the platform to assign a proportion of orders to each of high-performing and low-performing drivers.

		Period 1	Period 2
Scenario A:	W_L	${}^A P_1^A$	${}^A P_2^A$
Without preferential algorithm	W_H	${}^A P_2^A$	${}^A P_2^A$
Scenario B:	W_L	0	0
With preferential algorithm	W_H	${}^B P_1^B$	${}^B P_2^B$

In this simple model, we assume there is no fixed cost of working, and hence the decisions in the two periods are independent.[28] Therefore in scenario A, the labor supply decision in $t \in \{1; 2\}$ is

$$S_t(P_t^A) = M_t \quad \frac{\exp({}^A P_t^A)}{\exp({}^A P_t^A) + \exp(O_t)}:$$

The platform's decision then becomes

$$\max_{P_t^A}(1 \quad {}^A) P_t^A \quad \min\{D_t(P_t^A); S_t^A(P_t^A)\}:$$

In scenario B, however, only working in both periods generates positive wages for drivers. Thus, the labor supply decision becomes

$$S_1^B = S_2^B = S^B(P_1^B; P_2^B) = M \quad \frac{\exp({}^B(P_1^B + P_2^B))}{\exp({}^B(P_1^B + P_2^B)) + \exp(O_1 + O_2)}:$$

The platform's decision is

$$\max_{P_1^B; P_2^B}(1 \quad {}^B)P_1^B \quad \min\{D_1(P_1^B); S^B(P_1^B; P_2^B)\} + (1 \quad {}^B)P_2^B \quad \min\{D_2(P_2^B); S(P_1^B; P_2^B)\}:$$

First, we show the benefit of using a preferential algorithm. Fixing demand in each period by setting $P_t^A = P_t^B; t \in \{1; 2\}$, we show how the cost of labor changes in the two scenarios.[29] Figure C.1 shows the difference in labor cost with or without a preferential algorithm when reservation values $\{O_1; O_2\}$ change. The results show that when reservation values are below a certain threshold, using a preferential algorithm results in lower labor cost (negative). However, labor cost savings decrease as reservation values increase.

In practice, the commission fee is constantly fixed at around 20%. Therefore, we next calculate the platform's profit in equilibrium under each scenario when $_A = \quad _B$.[30] Figure C.2

[28] In our full model in Section 5, we assume that there is a warm-up cost to start working.

[29] Specifically, we first solve for the platform's optimal pricing decision without a preferential algorithm and obtain P_1^A and P_2^A. Then, we set $P_t^B = P_t^A$ and find the $_B$ that fulfills the demand for rides.

[30] Appendix ?? shows the details of how to calculate the platform's maximum profit under each scenario.

Figure C.1: Di erence in Labor Cost With and Without Preferential Algorithm

shows the di erence in platform pro t between scenarios A and B when reservation values f $O_1; O_2$g change. The results show that, when the reservation values increase, the bene t from forcing drivers to work in both periods decreases. When the reservation values are high, the pro t from scenario B is lower than that of scenario A. Therefore, the main intuition is consistent with our ndings above. When the reservation values are low, prioritizing high-performing drivers who work both periods bene ts the platform.

Figure C.2: Di erence in Platform Pro t With and Without Preferential Algorithm

We further examine how demand elasticity a ects the platform's incentives. We still x $_A = _B$, and Figure C.3 shows the di erence in platform pro t (with versus without the preferential algorithm) for di erent demand elasticities in each of the two periods. Panel (a) shows that platform pro t decreases with the preferential algorithm when demand becomes more elastic. This is because now consumers are more sensitive to prices, and hence the platform has to charge lower fares and generate a lower pro t. However, panel (b) shows that the di erence in platform pro t in the two scenarios increases when demand is more elastic. The reason is that now the platform bene ts more from the lower labor cost and is able to lower ride fares when prioritizing high-performing drivers.

In conclusion, platforms achieve higher revenues by requiring drivers to work certain schedules. The bene t of using a preferential algorithm is larger when driver reservation

(a) Platform Profit With Preferential Algorithm (b) Difference in Platform Profit (With - Without)

Figure C.3: Platform Profits When Changing Elasticity of Demand

values are low and when rider demand is more elastic compared to not using a preferential algorithm.

D 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.
- **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

[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.

driving distance are de ned to be proportional to each hour. For instance, suppose an order starts at 8:50 and nishes 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.

E Summary Statistics: Orders and Transactions

Table E.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 E.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 di erent platforms if they pay di erent 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 E.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 E.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 E.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 di erent 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 E.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 6th to 10th, 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 E.1: Orders, Transactions, Precipitation, and Temperature across Days

F Additional Regression Tables on Wage Di erentials

Appendix F contains additional regression tables for robustness checks, and veri es driver demographics that may have explanatory power for wage di erentials. Table F.1 reports how the driver's hourly wage depends on the fraction of di erent time intervals. We nd that drivers' hourly wages are higher when they work more during midday and at night. Table F.2 shows that, given their work schedule, there is little evidence of wage di erentials 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 signi cance of gender, it is economically insigni cant in determining wage rate. In contrast, the coe cients on birth city and age re ect work schedule variation across driver groups conditioning on the rst two variables. These results motivate controlling for age and birth city in our empirical analysis.

Table F.1: Hourly Wage by Di erent 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 xed e ects, origin district xed e ects, and destination district xed e ects. Standard errors are in parentheses. *** $p < 0.01$.

Table F.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. *** $p<0.01$.

G 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. 3^{rd}, 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 G.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 G.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 G.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

H 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 H.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.

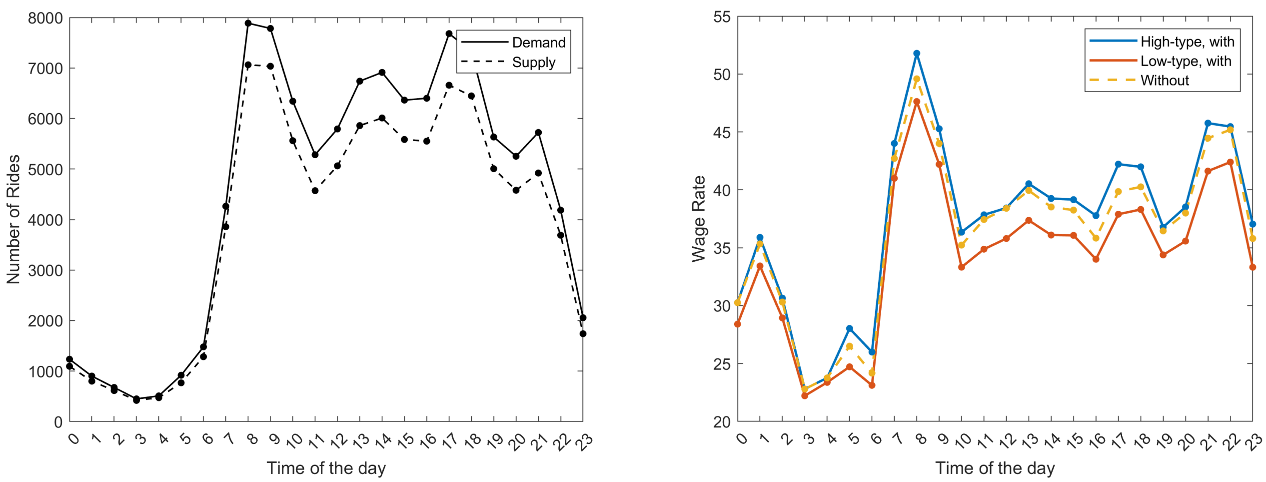

Figure H.1: Results from Eliminating the Wage Differential between W^H and W^L

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 H.2 shows the elasticity of labor supply corresponding to the elimination of the wage differential of treatment hour h.