Wage Elasticity of Labor Supply in Real-Time Ridesharing Markets: An Empirical Analysis

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Abstract

The prominence of real-time ridesharing services, such as Uber and Lyft, has dramatically changed the landscape of traditional industries. In this study, we provide a comprehensive analysis on the wage elasticity of labor supply in real-time ridesharing markets using data from a major ridesharing platform in China. By exploiting an exogenous shock from uneven driving restrictions as an instrumental variable, we find a negative labor supply elasticity for ridesharing drivers, suggesting that drivers tend to drive less during days with higher average hourly wage. This surprising finding is consistent with the behavioral income-targeting model based on the theory of reference-dependent preferences: Drivers have heuristic daily targets for total earnings and are more motivated to supply labor when they are below their income target than above it. Therefore, they work less on days when earnings per hour are high and quit the market once their income target is reached. In addition, we find that taxi drivers are more rational and are less affected by the income target. What is more interesting is that the labor supply elasticity is less negative for more experienced and patterned ridesharing drivers, which implies that drivers are more rational when they have repeated opportunities of learning. Estimating labor supply elasticity is critical to understand the economic efficiency of various surge pricing algorithms and driver subsidization programs for ridesharing platforms and policy makers. Our research suggests that a uniform price surging or driver subsidization to all ridesharing drivers may not incentivize labor supply of drivers effectively. A more efficient approach is to implement personalized price surging algorithms and driver subsidization programs targeting more experienced and patterned drivers.

Keywords: Labor supply elasticity, Ridesharing, Income target, Reference-dependent preferences

1. Introduction

1.1 Motivations

The unprecedented growth of ridesharing services, such as Uber and Lyft, has reshaped the traditional taxi industry by matching passengers and drivers in real time. More than 460,000 drivers in the United States

actively drove with Uber as partners by the end of 2015. The number of active Uber drivers approximately doubled every six months from the middle of 2012 to the end of 2015 (Hall and Krueger 2018). In 2016, the estimated number of Uber and Lyft drivers in San Francisco is 45,000, while the San Francisco Municipal Transportation Agency has issued only 2,026 taxi medallions (Jiang et al. 2018). In 2017, Uber and Lyft drivers were estimated to outnumber taxis 4 to 1 in New York City.[1]

A unique feature of innovative ridesharing services, or more broadly, new gig economy, is the flexibility on the labor supply side (Chen et al. 2017, Huang et al. 2017, Burtch et al. 2018, Kanat et al. 2018). The traditional taxi industry is heavily regulated: In many cities, the number of taxi drivers is limited by a licensing regime (e.g., the number of medallions that are issued) and taxi fare prices are often set by regulatory bodies (Cramer and Krueger 2016, Jiang et al. 2018). In contrast, in ridesharing services, new information technologies reduce the transaction cost of providing labor flexibly. Rather than supply being fixed, ridesharing services offers partner drivers flexibility in both setting a customized work schedule and also adjusting it throughout the day: Drivers can enter and exit labor markets freely and flexibly (Chen et al. 2017).

Because of the flexibility of labor supply in gig economy, ridesharing platforms typically use surge pricing algorithms to induce labor supply during periods of high demand (Chen and Sheldon 2016). In markets with highly variable demand, such as ridesharing market, dynamic pricing can be used to equilibrate the market. When there are relatively more riders than drivers, ridesharing platforms employs dynamic pricing in the form of surge pricing: The surge pricing algorithm assigns a simple surge multiplier that multiplies the standard fare.

Conventional wisdom suggests that the surged prices can induce labor supply and lead to more efficient markets. However, the potential economic efficiency of a surge pricing mechanism depends critically on the supply inducing effect. The key empirical question is whether a higher level of wage can

[1] See https://ny.curbed.com/2017/1/17/14296892/yellow-taxi-nyc-uber-lyft-via-numbers (last accessed: May 19, 2018).

stimulate the supply side of the market effectively. If the supply inducing effect is not significant, then surge pricing can be simply a way of extracting consumer surplus: It is more about redistributing wealth rather than improving marketing efficiency. A New York Times article called surge pricing "high-tech gouging."[2] It is both theoretically and practically important to estimate the wage elasticity of labor supply precisely. In this study, we provide a comprehensive analysis on the wage elasticity of labor supply in the new real-time ridesharing services using data from a major ridesharing platform in China. We also dig deeper into the heterogeneous effects of driving experience and driving patterns on labor supply elasticity and offer insights for researchers and practitioners regarding how to effectively implement personalized price surging algorithms and driver subsidization programs based on driver characteristics and driving patterns to increase labor supply in ridesharing markets.

1.2 Research Questions and Contributions

Prior literature has offered two different frameworks for labor supply decisions of workers: rational life cycle model and behavioral income-targeting model (Camerer et al. 1997). The predictions on the sign of labor supply elasticities from these two models are opposing, and each has gained empirical support to certain degree. The classical (fully rational) life cycle model of labor supply predicts a positive price elasticity of labor supply: As wages increase, individuals supply more labor. The underling logic is that workers maximize their lifetime utilities in a multi-period optimization problem. A temporary wage increase will cause workers to supply more labor now in exchange for future leisure when the opportunity cost of leisure is lower.

In contrast, the behavioral income-targeting model rooted in the reference-dependent preferences theory in behavioral economics (Tversky and Kahneman 1991). In an influential and seminal study, Camerer et al. (1997) empirically find a negative price elasticity of labor supply in taxi industry: As wages for a day increase, taxi drivers drive less total hours. This surprising empirical result can be justified in the

[2] See https://www.nytimes.com/2014/01/12/magazine/is-ubers-surge-pricing-an-example-of-high-tech-gouging.html (last accessed: May 20, 2018).

framework of income-targeting. Taxi drivers have daily, heuristic targets for total earnings and work until the target is reached, and hence they work less on days when earnings per hour are high. This explanation is consistent with the theory of reference-dependent preference (Tversky and Kahneman 1991, Ordóñez et al. 2009). The theory of reference-dependent preference postulates a kink in an individual's utility curve around a contextual reference point, where losses relative to this point are weighted more heavily than gains. In the context of taxi drivers, Camerer et al. (1997) argue that taxi drivers have a reference point (target) for daily income. Since losses are weighted more heavily than gains, taxi drivers are more motivated to supply labor when they are below their income target than above it. Therefore, on days when wage rate is lower, taxi drivers tend to work more to reach the target, and on days when wage rates is higher, taxi drivers tend to work less and quit the market once the target is reached.

Prior empirical literature has not reached a consensus on the direction of labor supply elasticity in traditional taxi industry. Chou (2000) and Crawford and Meng (2011) find support for income targeting (reference-dependent preference) using taxi driver data from Singapore and New York City, and confirm the finding in Camerer et al. (1997). However, Farber (2005, 2008, 2015) question the empirical implementation of Camerer et al. (1997) and conclude that income targeting does not play an important role determining the labor supply of taxi drivers in New York City. Most of these studies have mainly focused on labor supply in the traditional taxi industry. To the best of our knowledge, little is known about the labor supply elasticity in the new ridesharing services, the heterogeneity of labor supply elasticity, as well as a comparison of elasticities of labor supply for ridesharing and taxi drivers using data from the same city and the same time period.

In order to systematically bridge this research gap, we begin by asking our first research question: (1) *How to precisely estimate the wage elasticity of labor supply for ridesharing drivers?* Although Camerer et al. (1997) is highly influential, as mentioned earlier, the literature has not converged on whether the labor supply elasticity for taxi drivers is positive or negative. There are two empirical challenges in identifying the true elasticity of labor supply for drivers. First, in Camerer et al. (1997), taxi drivers' working hour data

comes from drivers' hand-written trip sheets.[3] Farber (2005, 2008) point out that the measurement error from trip sheets of taxi drivers may lead to spuriously negative elasticities. One advantage of our ridesharing data is that due to the development of information technologies, the ridesharing mobile application accurately monitors drivers' activities in real time, and the measurement error in recording working hours should be minimal in our context.

Second, a typical way of estimating labor supply elasticity is based on a regression of daily working hours on average hourly wage (the impact of wages on working hours). However, drivers' labor supply decision (working hours) is an endogenous result of optimization with drivers' preferences on the trade-off of work and leisure. When wage rate of driving is high, it is likely to be holidays on which drivers want to enjoy quality family time. Therefore, the usual estimates of labor supply elasticity may be misleading, and we may observe a spuriously negative elasticity: a negative correlation between working hours and wage. In this study, we exploit an exogenous shock from uneven driving restrictions as an innovative instrumental variable (IV) to address the endogeneity of drivers' labor supply. The rational of our IV is based on the exogenous shock from government regulation: In order to alleviate both air pollution and travel congestion, the Beijing municipal government started implementing driving restrictions since the 2008 Beijing Olympics. Vehicles are categorized into five groups based on the last digit of the license plate: 0&5, 1&6, 2&7, 3&8, and 4&9. Then each group is assigned to one weekday every thirteen weeks. Interestingly, these exogenous driving restrictions are not uniform across weekdays. Because "4" is an unlucky number in traditional Chinese culture, there are fewer vehicles whose license plate is ended with "4" (Viard and Fu 2015, Gu et al. 2017). As a result, there tends to be more ridesharing drivers on the weekday when vehicles with license plate ending with 4 or 9 are restricted. This exogenous variation can be an IV for hourly wage of drivers who are not restricted on these days because it is negatively correlated with drivers' hourly wage: (i) With fewer ridesharing drivers being restricted, the supply in ridesharing market increases, and (ii) With

[3] Taxi drivers were required to fill out trip sheets by hand to record and store information on paper about each fare.

fewer private cars being regulated, people are more likely to use their own cars as a travel option rather than using ridesharing services.

Using IV analysis, we find a negative labor supply elasticity for ridesharing drivers, which suggests that drivers tend to drive less during days with higher average hourly wage. Therefore, the behavioral income-targeting model based on the theory of reference-dependent preferences seems to provide a better explanation for ridesharing drivers' daily labor supply decisions. Using conditional logit and survival models, we also show that the likelihood of quitting market for ridesharing drivers is significantly associated with the income already earned, which provides additional evidence for the behavioral income-targeting model.

Past research has not directly compared elasticities of labor supply for ridesharing and taxi drivers using data from the same city and the same time period, which leads to our second research question: (2) *What is the difference between the labor supply elasticity for ridesharing drivers and taxi drivers?* As mentioned earlier, the literature has not converged on the labor supply elasticity for taxi drivers. Using our IV based on the uneven driving restrictions, we find that the labor supply elasticity for taxi drivers is not significantly different from zero. In other words, taxi drivers are more rational and are less affected by behavioral income targeting. Taxi drivers, who are professional drivers, tend to have more experience of providing rides and are more motivated to maximize their income since this is the only or main income. Compared with ridesharing drivers, taxi drivers are able to make more rational decisions in terms of their labor supply decisions. In contrast, ridesharing drivers are mostly part-time drivers and focus on earning pin money. Therefore, these drivers are more likely to have reference-dependent preferences: They have a daily income target, and an increase in hourly wage makes them reach their targets sooner and quit driving for the day.

To gain a deeper understanding of driver heterogeneity, we ask our third research question: (3) *How does labor supply elasticity vary with drivers' characteristics and driving patterns?* The rational life cycle model and behavioral income-targeting model predict opposing signs of labor supply elasticity. Both

cases are theoretically plausible, presenting a viable opportunity for empirical testing. In fact, both theories have gained support from empirical studies in different contexts. We suspect that driver heterogeneity plays an important role: Different types of drivers may exhibit different behaviors. Our empirical results provide a complete picture of labor supply elasticity in ridesharing markets by reconciling these two different models in a unified framework: We find that the labor supply elasticity is less negative for more experienced and engaged ridesharing drivers. For some experienced and engaged ridesharing drivers, the labor supply elasticity could be positive. Also, in terms of driving patterns, labor elasticity is less negative for pattern drivers who regularly work on certain times in a week than for random drivers. Overall, our findings bridge the two perspectives in prior studies and suggest that ridesharing drivers who are new to the market are more likely to have reference-dependent preferences and set a behavioral income target. However, setting income targets is inefficient because these drivers are systematically leaving "money on the table": They work less on high-wage times and work more on low-wage times. We find that the behavior of more experienced ridesharing drivers is more consistent with the rational life cycle model possibly because of repeated opportunities of learning.

2. Literature Review

In this section, we review the literature from three aspects: (i) individual driver behavior, (ii) labor supply in sharing economy, and (iii) the societal and economic outcomes of sharing economy. We also highlight our contributions by comparing and contrasting our work with past studies.

2.1 Individual Driver Behavior

Prior literature on labor supply of taxi drivers has primarily focused on estimating labor supply elasticity of taxi drivers (Camerer et al. 1997, Crawford and Meng 2011, Farber 2005, 2008, 2015). Recently, several studies look at drivers' learning behavior in different contexts. Zhang et al. (2016) find strong heterogeneity in taxi drivers' learning behavior and driving decisions. Zheng et al. (2016) examine how two-sided sales promotion from platforms interacts with taxi drivers' learning dynamically. Our research investigates the

labor supply elasticity of ridesharing drivers, and shows that the labor elasticity is less negative for more experienced and patterned ridesharing drivers, suggesting that learning plays an important role in the debate on rational life cycle model versus behavioral income-targeting model.

2.2 Labor Supply in Sharing Economy

The new sharing economy represents a shift away from traditional employment relationships to a more flexible and customized work schedule. Chen et al. (2017) estimate the surplus of ridesharing drivers generated from work flexibility. Angrist et al. (2017) examine the economic value of ridesharing work opportunities for drivers by focusing on differences in the compensation arrangements available to traditional taxi and ridesharing drivers. Cook et al. (2018) investigate labor supply choices and earnings among more than a million ridesharing drivers on Uber in the U.S. and find a roughly 7% gender earnings gap amongst drivers. Our paper focuses on estimating the labor supply elasticity and the heterogeneous effects of driving experience and driving patterns on the labor supply elasticity in ridesharing markets.

2.3 The Societal and Economic Outcomes of Sharing Economy

Our study is related to a stream of literature examining the societal and economic outcomes of sharing-economy platforms. Li et al. (2016) empirically estimate the impact of Uber entry on traffic congestion in the urban areas of the United States. Greenwood and Wattal (2017) examine the effect of ride-sharing services on the rate of alcohol related motor vehicle fatalities. Gong et al. (2017) find that Uber entry is associated with a considerable increase in new vehicle ownership in China. Zervas et al. (2017) show a negative causal impact of Airbnb entry on hotel revenue. Burtch et al. (2018) demonstrate a negative and significant relationship between Uber entry and entrepreneurial activities. In our study, we find that the labor supply in ridesharing markets tend to be reference dependent, which is critical to understand the economic efficiency of various surge pricing algorithms in ridesharing markets.

3. Data

In this section, we use data on trip information of Beijing taxi and ridesharing drivers to explore the relationship between hours that drivers choose to work each day and the average daily wage. Driver's trip information may be challenging to achieve in traditional taxi industry given the decentralized system. With the rise of ridesharing technology companies, we are able to get access to each trip's detailed information with minimal errors through data from mobile applications.

We obtained a novel panel dataset from one of the major ridesharing companies headquartered in China. The data include a random sample of drivers' driving information in Beijing from Dec 3, 2015 to Jan 3, 2016. Specifically, our data includes drivers' information from two different services on the platform: taxi and express. For the taxi service, the company partners with more 200 taxi companies in China so that consumers could order taxi services online; for the express service, it is a two-sided platform (similar to peer-to-peer ridesharing services, such as Uber and Lyft) that matches consumers and private drivers based on its dispatch system and route planning.

By year 2015, there are about 66,600 cabs in Beijing and the number has not changed significantly for about 10 years.[4] There are two types of taxi drivers in Beijing at present: lease-drivers and owner-drivers. Among all cabs, only about 1,000 of them are owned by taxi drivers.[5] In other words, the majority of (more than 98%) taxi drivers need to pay their taxi company a deposit in the beginning of the contract, which is about half of the car's market value. In addition, these drivers also need to pay their taxi company a fixed amount of administrative fee. These drivers tend to have more driving experience and their labor supply is less flexible since they are full-time taxi drivers.

Express service was launched in China in 2015, which is a platform that allows individuals to provide customized transportation services using their own cars. In 2016, the company has over 15 million

[4] Data source: http://politics.people.com.cn/n/2012/0816/c1001-18753269.html (last accessed: January 20, 2018).
[5] Data source: http://gd.qq.com/a/20110722/000100.htm (last accessed: January 20, 2018).

registered drivers. One of the main motivations for drivers to join the platform is to make money on the side to subsidize household. Therefore, we expect these private drivers' labor supply to be more flexible.

In our analysis, the measure of hours worked is obtained directly from drivers' information table. Specifically, the drivers need to log on the mobile application to receive an order from customers on the platform, which is recorded by the system. Hence, we use the period that each driver has been logged on as a measure of this driver's labor supply. On the other hand, drivers' total revenue per day was calculated by adding up the fares of trips from drivers' transaction table. The average hourly wage is total revenue divided by hours worked.

Our data includes 971 taxi drivers with 45,870 orders and 2,954 ridesharing drivers with 308,305 orders within one-month period. Specifically, for both services, we know each driver's detailed trip information each day, including a trip's start and end time, start and end locations (geographical coordinates), price, and customer ID. In addition, we also have knowledge of each driver's registration date, daily logged on time in the system, and express service drivers' car model information.

We also composed some additional variables to better characterize each driver. First, using the information of each driver's registration date, we created the "age" of each driver on the platform by counting the number of days since registration. Second, based on each trip's start and end location, we generated a mobility variable based on radius of gyration, indicating whether the activity space of the vehicle is large or not. Radius of gyration has been widely used in geographical literature to represent the spatial dispersion of an individual's daily activities (Gonzalez et al. 2008). Specifically, we collected geographic coordinates of all trips' points of departure and destination. We then obtained the geometric center (centroid) by calculating the arithmetic means of all latitude and longitude coordinates. The mobility measure for driver *i* is created using the following formula:

$$mobility_i = \frac{1}{N_i}\sum_{n=1}^{N_i} \sqrt[2]{(longitude_{in} - c\_long_i)^2 + (latitude_{in} - c\_lat_i)^2},$$

where c_long_i and c_lat_i are the coordinates of the geometric center and N_i is the number of trips per driver has in our dataset.

We also collected Beijing's daily weather and air pollution information online, including high and low temperature, wind speed, precipitation, visibility, air quality index, and PM 2.5.[6] The summary statistics of the key variables are presented in Table 1.

Table 1 Summary Statistics

	Obs.	Mean	Median	Std. dev
Taxi drivers (Obs. 971)				
Hours worked	15836	7.62	7.45	3.67
Total revenue (¥)	15836	150.64	122	115.55
# trips per day	15836	2.90	2	2.16
Age	15836	1128.75	1120	82.56
Mobility	971	0.66	0.099	2.63
Low temperature (°F)	15836	22.43	22	4.98
Wind speed (mph)	15836	5.29	4	4.16
Visibility (miles)	15836	4.36	2.8	4.46
precipitation	15836	0.11	0	0.31
Air quality index	15836	183.69	168	115.85
PM 2.5	15836	147.24	127	109.02
Express drivers (Obs. 2954)				
Hours worked	32014	6.59	6.5	3.79
Total revenue (¥)	32014	181.24	151.3	140.73
# trips per day	32014	9.63	9	6.93
Age	32014	258.75	263	70.91
Mobility	2954	0.085	0.066	0.20
Low temperature (°F)	32014	22.35	22	4.83
Wind speed (mph)	32014	5.17	4	4.05
Visibility (miles)	32014	4.32	2.8	4.32
Precipitation (dummy)	32014	0.11	0	0.32
Air quality index	32014	178.31	168	113.58
PM 2.5	32014	142.37	127	107.36

Drawing upon the summary statistics, we find some interesting patterns. First, taxi drivers tend to work on more days than express drivers in our data set. On average, each taxi driver worked 16.33 days on the platform during the one-month period while express drivers only worked 10.84 days. Similarly, taxi drivers drove 7.62 hours per day on average, which is higher than 6.59 hour per day for express drivers. The statistics also showed that taxi drivers tend to move in a larger area. This is in line with our expectation since many of express drivers have other full-time jobs and ridesharing is their way to earn pin money. In

[6] Data source: https://www.wunderground.com/history/ for historical weather information and http://www.tianqihoubao.com/aqi/beijing-201512.html for historical air pollution information.

addition, taxi drivers are "older" (more experienced with the mobile application) compared with express drivers. This is because this company launched the taxi service back in 2012 and the express service was added in 2014. For the weather information, most of the 31 days in our data set did not have precipitation. However, there were multiple days during this period with severe air pollution. Actually, Beijing issued first ever pollution "red alert" in December 2015.[7] Air quality index (AQI) is a weighted average of the concentrations of five major pollutants: O_3, NO_2, SO_2, PM 2.5 (particles with an aerodynamic diameter less than 2.5 μm), and PM 10 (particles with an aerodynamic diameter less than 10 μm). AQI ranges from 0 to 500, with higher value indicating greater level of air pollution.

We first use the raw data to explore the relationship between drivers' hours worked and hourly wage. For each of the two data sets, we calculate the simple correlation between (log) hours and (log) hourly wages. The correlation for taxi drivers is -0.3415 and it for express drivers is -0.1446.

4. Empirical Model and Results

4.1 Baseline Model

To estimate the labor supply function, the dependent variable in our model is each driver's log number of hours being logged on the system on a day. The main independent variable of interest is log hourly wage for each driver on a day when he or she chooses to work. Other control variables include drivers' age information, weather information, and day of week dummies. To further control for driver-level, time invariant unobservable characteristics, we include driver fixed effects and the standard errors are also corrected to account for clusters. The regression results are reported in Table 2. We find negative labor supply elasticities for both taxi and express drivers. This means that drivers tend to drive less during days

[7] Data source: http://www.bbc.com/news/world-asia-china-35026363 (last accessed: January 20, 2018).

with higher average hourly wage. Based on these results, it seems that income reference-dependent preferences may have been a better theory to understand ridesharing drivers' daily labor supply decisions.

Table 2. Labor Supply Elasticity: Basic Analysis (OLS)

	Taxi drivers		Express drivers	
	(1) w/o fixed effects	(2) with fixed effects	(3) w/o fixed effects	(4) with fixed effects
Log hourly wage	-0.264***	-0.174***	-0.175***	-0.110***
	(0.00731)	(0.00854)	(0.00668)	(0.0103)
Log_age	0.145***	-0.514	0.0910***	0.0197
	(0.0518)	(0.903)	(0.0109)	(0.0628)
Low temperature	-0.00123	-0.00255**	-0.00453***	0.000440
	(0.00115)	(0.00127)	(0.00117)	(0.00107)
Wind speed	0.00775*	0.00975**	0.0214***	0.0106***
	(0.00407)	(0.00440)	(0.00392)	(0.00281)
Visibility	-0.0103***	-0.0136***	-0.0201***	-0.0122***
	(0.00368)	(0.00412)	(0.00355)	(0.00253)
Precipitation=1	-0.0429**	-0.0398**	-0.0312	-0.0246
	(0.0202)	(0.0164)	(0.0231)	(0.0158)
PM2.5	-0.000294	-0.000315	-0.000607	-0.000529
	(0.000583)	(0.000517)	(0.000569)	(0.000380)
AQI	0.000150	0.000118	0.000618	0.000640*
	(0.000570)	(0.000495)	(0.000555)	(0.000373)
Fixed effects	No	Yes	No	Yes
Day of week dummies	Yes	Yes	Yes	Yes
Constant	1.615***	6.035	1.735***	1.773***
	(0.367)	(6.366)	(0.0756)	(0.356)
Number of drivers	971	971	2,954	2,954

Clustered Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

We also have interesting findings for other control variables. For the weather variables, the results show that low visibility condition will decrease drivers' daily driving time. This can be explained by the fact that low visibility may decrease drivers' driving experience and increase the possibility of traffic accidents (Farber 2015). On the other hand, low temperature and high wind speed are factors that will increase drivers' daily driving hours. It is possible that severe weather conditions such as low temperature and strong wind drive more people to choose cabs or express car services rather than walking or public transportation. Surprisingly, we did not find significant effects of air pollution variables.

4.2 Instrumental Variables

One main concern of the basic empirical results is the potential endogeneity problem of the log hourly wage. There may be measurement errors such as drivers may forget to log out of their mobile applications at the

end of their work. It is also possible that there are other variables or events influencing both the hours drivers work and the average hourly wage that we do not observe. This challenge could be alleviated by finding IVs that are correlated with hourly wage but do not directly relate to the decision of labor supply. In this study, we adopt two IVs: (i) summary statistics of hourly wage distribution, and (ii) uneven driving restrictions.

4.2.1 Instrumental Variable I: Summary Statistics of Hourly Wage Distribution

One widely accepted group of IVs in the literature is summary statistics of other drivers' hourly wage distribution on the same day (Camerer et al. 1997, Farber 2015). Specifically, we use the mean and the 25th, 75th percentile of hourly wage distribution of other drivers on the same day as our IVs. These IVs should be correlated with one individual's average hourly wage in the same day since many environmental variables tend to impact all drivers on the road. However, as variables summarize other drivers' wage information, they should not directly affect an individual's labor supply decision. From Table 3, we can see that the first-stage F statistics for our regressions are above 30, indicating that our instrumental variables are not weak.

With the help of the instrumental variables, we use the two stage least squared method (2SLS) to estimate the labor supply function. The main results as well as the first-stage estimates are reported in Table 3. The results are quite interesting. For taxi drivers, the coefficient of log hourly wage is not statistically significant. This means taxi drivers have a relatively stable labor supply no matter what hourly wage is. On the other hand, for express drivers, we still find significant negative labor supply elasticity: A percent increase in hourly wage leads to almost 0.2 percent decrease in labor supply. The observed different behaviors between taxi drivers and express drivers can be explained as follows: Taxi drivers, who are professional drivers, tend to have more experience of providing rides and are more motivated to maximize their income since this is the only or main income. As a result, compared with express drivers, taxi drivers are able to make more rational decisions in terms of their labor supply decisions. In contrast, express drivers are mostly part-time drivers and focus on earning pin money. Therefore, these drivers are more likely to

have reference-dependent preferences: They have a daily income target, and an increase in hourly wage makes them reach their targets sooner and quit driving for the day.

Table 3. Labor Supply Elasticity*:* Wage Distribution IVs

	Taxi drivers		Express drivers	
	(1) First-stage	(2) Main regression	(3) First-stage	(4) Main regression
Log hourly wage		-0.0791		-0.200***
		(0.0534)		(0.0299)
Log_age	-0.0521	0.156	0.0303	0.0176
	(1.583)	(0.994)	(0.0483)	(0.0622)
Low temperature	0.00164	-0.00208	0.000734	0.000454
	(0.00214)	(0.00131)	(0.000828)	(0.00107)
Wind speed	-0.00176	0.00937**	-0.00480*	0.0113***
	(0.00532)	(0.00448)	(0.00248)	(0.00283)
Visibility	0.00234	-0.0135***	0.00210	-0.0131***
	(0.00487)	(0.00416)	(0.00215)	(0.00256)
Precipitation=1	-0.0342	-0.0254	-0.00482	-0.0325**
	(0.0293)	(0.0179)	(0.0134)	(0.0160)
PM2.5	0.000158	-0.000251	0.000262	-0.000669*
	(0.000740)	(0.000532)	(0.000327)	(0.000381)
AQI	-1.11e-04	4.44e-05	-0.000315	0.000788**
	(0.000735)	(0.000511)	(0.000319)	(0.000375)
Mean	8.54e-5		0.205	
	(0.00436)		(0.255)	
25th percentile	0.453***		0.367***	
	(0.0985)		(0.130)	
75th percentile	0.360***		0.373**	
	(0.135)		(0.172)	
Fixed effects	Yes	Yes	Yes	Yes
Day of week dummies	Yes	Yes	Yes	Yes
Constant	-1.319	1.065	-0.0456	2.072***
	(11.526)	(7.062)	(0.313)	(0.365)
First-stage F statistics	36.98		119.96	
Number of drivers	971	971	2,954	2,954

Clustered Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

4.2.2 Instrumental Variable II: Uneven Driving Restrictions

We also exploit an exogenous shock from the uneven driving restrictions as an instrumental variable to further confirm our previous results. In order to alleviate both air pollution and travel congestion, the Beijing municipal government started implementing driving restrictions since the 2008 Beijing Olympics. After that, the driving restrictions have been relaxed multiple times, and the current restriction (since April 11, 2019) prevented vehicles from entry within the 5th Ring Road (excluding the 5th Ring Road) one weekday per week from 7am to 8pm. In these driving restrictions, vehicles are categorized into five groups based on

the last digit of the license plate: 0&5, 1&6, 2&7, 3&8, and 4&9. Then each group is assigned to one weekday every thirteen weeks. The following vehicles are not applied to the driving restrictions: police cars, fire trucks, ambulances, buses, taxis, and other vehicles authorized by the government. Specifically, from October 11, 2015 to January 9, 2016 (our sample period), the last digits of license plates that were restricted from Monday to Friday are the following pairs: 4&9, 5&0, 1&6, 2&7, and 3&8.

One interesting finding which is widely reported in media is that driving restrictions are not uniform across weekdays (Gu et al. 2017). Because "4" is an unlucky number in traditional Chinese culture, there are fewer vehicles whose license plate is ended with "4". This observation has been verified by survey data in Gu et al. (2017) and observational data in Viard and Fu (2015). As a result, there is an exogenous shock on the weekday when vehicles with license plate ending with 4 or 9 are restricted.[8] This exogenous variation can be an instrumental variable for drivers' hourly wage from both supply and demand perspectives: (i) With fewer express drivers being restricted, there are more ride sharing service providers available, leading to an increase in market supply; and (ii) with fewer private cars being regulated, people who own cars are more likely to use their own cars as a travel option. Hence, there are fewer customers who are looking for ridesharing service, which is a demand reduction. Combining both the supply and demand effects, we expect log hourly wage to be lower on Mondays during this time period, which is validated by our data analysis in Columns 1 and 3 of Table 4. Therefore, we use the weekday when 4&9 are restricted as an alternative IV, which is negatively correlated with our main independent variable, log hourly wage.

One challenge for this robustness check is to identify the restriction day for each ridesharing driver.[9] Based on our dataset, some drivers have received orders every day of week. Potential mechanisms to drive on restricted days include noncompliance and driving outside the 5th Ring Road. However, we believe that drivers' behaviors are inevitably influenced by the regulation. For example, because of the potential

[8] News link: http://www.yicars.com/c/bjqcxxwh/2017-11/3786.html. (Last accessed: February 4, 2018)
[9] Taxi drivers are excluded from the driving restriction.

punishment,[10] drivers may choose to only accept orders with shorter distance. As a result, in order to accurately estimate the labor elasticity, we would like to exclude the data from the restricted weekday for each driver (excluding noncompliance data).

Given the limited data we have, we do not have access to each driver's license plate to infer their restricted weekday directly. We identified drivers' day of restriction by their overall behaviors. Specifically, we summarized each driver's total number of orders and online time on each day of week. And we excluded a driver's data from the day of week which has the lowest number for either one of the two measures. Our results with the subsample and alternative IV are reported in Table 4. We can see the results are qualitatively equivalent to our main results.

Table 4. Labor Supply Elasticity: Uneven Driving Restriction IVs

	Taxi drivers		Express drivers	
	(1) First-stage	(2) Main	(3) First-stage	(4) Main
Log hourly wage		-0.0552		-0.291***
		(0.107)		(0.0656)
Log_age	-5.221***	2.358**	0.00554	0.0680
	(1.292)	(0.927)	(0.0506)	(0.0599)
Low temperature	-0.00284	0.000161	0.00598***	0.000864
	(0.00197)	(0.00123)	(0.000923)	(0.00122)
Wind speed	-0.00164	0.00543	-0.0103***	0.0155***
	(0.00451)	(0.00365)	(0.00217)	(0.00272)
Visibility	0.00667	-0.00653*	0.00474**	-0.0162***
	(0.00415)	(0.00356)	(0.00185)	(0.00233)
Precipitation=1	-0.112***	0.0304*	-0.0369***	-0.0132
	(0.0208)	(0.0172)	(0.0105)	(0.0121)
PM2.5	-0.00165***	-0.00109***	-0.00133***	-0.00134***
	(0.000600)	(0.000390)	(0.000290)	(0.000337)
AQI	0.00183***	0.000950**	0.00147***	0.00144***
	(0.000596)	(0.000380)	(0.000284)	(0.000335)
If_4&9	-0.108***		-0.221***	
	(0.0183)		(0.0125)	
Fixed effects	yes	yes	yes	yes
weekend dummies	yes	yes	yes	yes
Constant	39.542***	-14.53**	3.031***	2.119***
	(9.105)	(6.672)	(0.283)	(0.388)
Number of drivers	971	971	2,841	2,841

Clustered Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

[10] The fine of driving violation is ¥200. Data source: https://en.wikipedia.org/wiki/Road_space_rationing_in_Beijing. (Last accessed: February 4, 2018)

4.3 Robustness Checks

4.3.1 Analysis using Session Data

One concern using each driver's daily working hour and income as analysis unit is that a typical workday may not correctly represent drivers' supply choice. Since there are no organizational constraints on working hours for the sharing economy, drivers have the flexibility to choose when to start and stop driving. For example, one driver may choose to work from 10 pm to 2 am because there is high demand among people who leave nightclubs in downtown. Similarly, a driver may serve as an express driver twice a day during morning and evening perk. As a result, in order to precisely estimate the labor supply elasticity, we complement the analysis with daily sessions following a modified approach used in Chen and Sheldon (2016).

We define a session as the cluster of trips that take place without a break of more than 4 hours.[11] The "length" of a session is defined as the time interval between the end time of the last trip and the beginning time of the next trip. And the income of a session is calculated by the sum of all trips within the session. Table 5 shows the average length of session, income and total number of trips per express driver. We repeat the basic empirical analysis using the session data and the results are reported in columns 1-2 of Table 6. The basic results are consistent. For the instrumental variables, for each session, we use the distribution of hourly wage for trips happened during the session time from other drivers. The results are in columns 3-4 of Table 6.

Table 5. Summary Statistics of Session Hour and Income

	Mean	Median	s.d.	obs
Session hour	5.08	3.91	4.43	41519
Session income	140.80	101.5	129.85	41519
Number of trips	7.50	6	6.30	41519

[11] We also did analysis using a session defined as a cluster of trips that occur without a break of more than 2 hours. The results are qualitatively equivalent.

Table 6. Basic Results using Session Data

	OLS		2SLS	
	(1) w/o fixed effects	(2) With fixed effects	(3) First-stage	(4) Main regression
Log hourly wage	-1.241***	-1.214***		-1.067***
	(0.0105)	(0.0140)		(0.0486)
Log_age	-0.0186	-0.0314	-0.0439	-0.0245
	(0.0120)	(0.0813)	(0.0302)	(0.0810)
Low temperature	-0.00701***	-0.00361***	-0.001148***	-0.00325**
	(0.00123)	(0.00125)	(0.000572)	(0.00126)
Wind speed	0.0369***	0.0265***	0.00421**	0.0245***
	(0.00401)	(0.00342)	(0.00173)	(0.00349)
Visibility	-0.0352***	-0.0305***	-0.00556***	-0.0284***
	(0.00365)	(0.00311)	(0.00156)	(0.00320)
Precipitation=1	-0.0485*	-0.0573***	-0.0972***	-0.0516**
	(0.0258)	(0.0211)	(0.00989)	(0.0212)
PM2.5	-0.00315***	-0.00290***	0.000417*	-0.00281***
	(0.000620)	(0.000486)	(0.000249)	(0.000488)
AQI	0.00339***	0.00318***	-0.000465*	0.00307***
	(0.000607)	(0.000476)	(0.000247)	(0.000478)
Mean			-3.279**	
			(1.080)	
25th percentile			10.84***	
			(0.710)	
75th percentile			-1.034	
			(0.575)	
Fixed effects	No	Yes	Yes	Yes
Day of week dummies	Yes	Yes	Yes	Yes
Constant	5.467***	5.397***	-4.912***	4.861***
	(0.0842)	(0.461)	(0.281)	(0.487)
First-stage F statistics			172.27	
Number of drivers	2,960	2,960	2,960	2,960

Clustered Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

4.3.2 When to Stop Driving

Another analysis that can be complemental to the existing results is to estimate a driver's decision to continue or stop driving after a trip within a session. If a driver has reference-dependent preference, he or she is more likely to drop the session when the existing hourly average wage is higher.

To investigate if this is the case, we use both conditional logit model and Cox survival model. For the conditional logit model, we use the dummy indicates whether the trip is the last one within a session. For the Cox survival model, we use the length of time until a driver ends the driving session as duration. The results are placed in columns 1 and 3 of Table 7. In columns 1 and 3, we find that when the cumulative hourly wage is higher, drivers are more likely to end driving sessions, which supports that drivers has

reference-dependent preference. We also include the last trip's wage to see how it influences driver's decision in the analysis for columns 2 and 4 of Table 6. The estimated results show that, the coefficients of the cumulative average wage are still positive and significant.

Table 7. The Choice to End a Session

	Conditional Logit		Survival	
	(1)	(2)	(3)	(4)
Log cumulative online time	0.517***	0.261***		
	(0.0106)	(0.0121)		
Log cumulative hourly wage	0.180***	0.195***	0.194***	0.407***
	(0.0172)	(0.0164)	(0.0136)	(0.0141)
Log hourly wage of last trip		-0.388***		-0.467***
		(0.00566)		(0.00570)
Driver's log average session time			-1.154***	-1.139***
			(0.0100)	(0.00979)
Low temperature	0.00597***	0.00604***	0.00407***	0.00337***
	(0.00172)	(0.00178)	(0.00128)	(0.00123)
Wind speed	-0.0234***	-0.0230***	-0.00669	-0.00775*
	(0.00481)	(0.00463)	(0.00442)	(0.00421)
Visibility	0.0367***	0.0358***	0.0149***	0.0166***
	(0.00399)	(0.00381)	(0.00393)	(0.00375)
Precipitation=1	0.123***	0.129***	0.0497***	0.0602***
	(0.0263)	(0.0258)	(0.0226)	(0.0221)
PM2.5	0.00496***	0.00491***	0.00208***	0.00219***
	(0.000694)	(0.000515)	(0.000607)	(0.000587)
AQI	-0.00536***	-0.00535***	-0.00219***	-0.00234***
	(0.000680)	(0.000520)	(0.000590)	(0.000572)
Fixed effects	Yes	Yes	No	No
Day of week dummies	Yes	Yes	Yes	Yes

Clustered Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

4.4 Moderating Effects of Drivers' Characteristics and Driving Patterns

To further validate the behavioral income-targeting model, we investigate whether drivers with different levels of engagement in this business behaved differently, especially for ridesharing drivers. Based on the report released by the company, drivers on the platform have different motivations to provide service: from full-time drivers to driving for pin-money. As a result, we expect to find that those ridesharing drivers who are more engaged in this service have similar labor supply preference as taxi drivers.

Specifically, we have different measures of ridesharing drivers' engagement level: online time, earned money, and the vehicle's activity space. We created engagement dummies based on whether drivers' total online time, total earned revenue, or activity space during this one-month period are larger than the median values among all express drivers. Then we repeat the baseline analysis with interactions between log hourly wage and engagement dummies. The results are reported in the first three columns of Table 8. We can see the coefficients of log hourly wage are significantly negative, and the magnitudes are larger than those in Table 2. For the coefficients of three interactions, they are positive and statistically significant. These indicate that, compared with less engaged ridesharing drivers, the labor supply elasticity is less negative for more engaged ridesharing drivers. In other words, as ridesharing drivers become more experienced, they are more rational and are less likely to have reference-dependent preferences and to leave "money on the table." Some experienced ridesharing drivers can have a positive labor supply elasticity. This finding echoes Zhang et al. (2016) in which they find significant learning in individual decisions of drivers.

In addition to the drivers' engagement level, we also explore other drivers' characteristics. One advantage of ridesharing economy is that it provides drivers the opportunity of flexible schedule. Based on the company's business report, more than 30% of the drivers believe that ridesharing is a good opportunity for them to earn pin money to subsidize their main job. At the same time, more than 25% of the drivers also work full time on the platform in 2016. Drivers with different driving patterns may also have different preference. Drivers who regard ridesharing as their main income source and regularly work on the platform may maximize their income from a multi-period optimization problem. As a result, when the temporary hourly wage increases, these drivers may choose to lengthen working hours in the current time period. On the other hand, drivers who randomly use this platform to earn pin money are more likely to have an income target for a particular day or session. When the hourly wage is higher, these drivers may choose to quit driving early, leading to smaller number of working hours. Hence, we apply a k-means cluster analysis of the hours worked by drivers (Chen et al. 2017), attempting to classify drivers into groups based on their

driving patterns. Specifically, we construct an 84-degree vector for each driver, with each component representing the number of minutes the driver was active during the two-hour period of the week. We then apply a k-means clustering analysis for all the express drivers in our data set and set the number of clusters to be 3 based on the elbow method.[12] Basically, we run k-means clustering using *k* from 1 to 20 respectively, and for each value of *k*, calculate the sum of squared errors (SSE). All the SSE are reported in the line chart below in Figure 1. We can see that 3 is the "elbow" on the arm. This indicates that adding another cluster after 3 doesn't give much better modeling of the data.

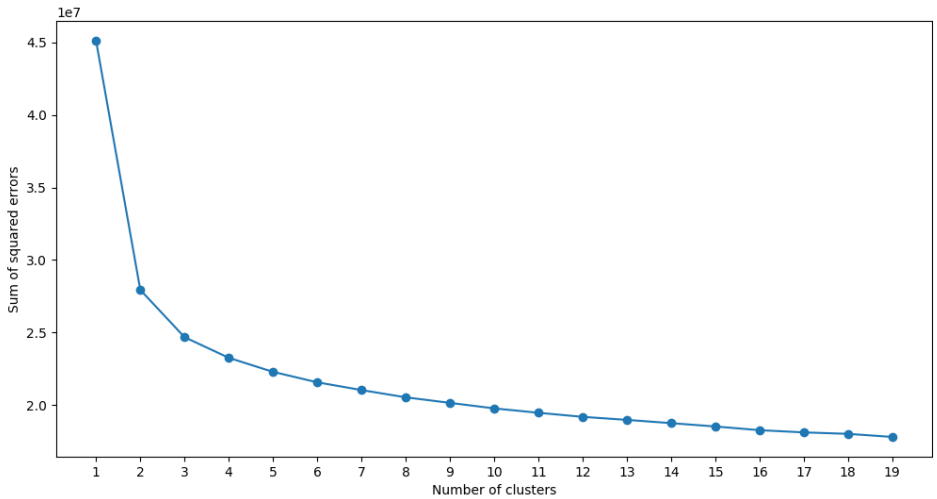

Figure 1. Optimal Number of Clusters for the K-Means Clustering

Based on the presented drivers' working pattern within a week, we can further put all drivers into two groups: random drivers and pattern drivers. For drivers in cluster 1, their average working time is significantly less than other drivers in clusters 2 and 3. Also, compared with drivers in the other two clusters, those in cluster 1 do not have a clear pattern in terms of mean fraction of drivers working that two-hour period of the week. As a result, we label the drivers in clusters 2 and 3 as pattern drivers (Pattern driver = 1) and drivers in cluster 1 as random drivers (Pattern driver = 0). We expect to see the coefficient of the

[12] Elbow method is a basic way to define the optimal number of clusters for k-means clustering. It tries to select the smallest number of clusters for the largest amount of data variation.

interaction between log hourly wage and pattern driver dummy to be positive. And the results in column 4 of Table 8 support our hypothesis.

Another feature of drivers is the automobile which they registered in the platform. In our data set, drivers' vehicles range from low end economy cars to luxury SUVs. Drivers with luxury cars or economy cars have different motivations on the platform. Drivers with relative luxury cars are mostly part-time drivers and focus on earning pin money. Therefore, these drivers are more likely to have reference-dependent preferences. We use vehicle engine displacement to categorize drivers, which correlates with the amount of power generated and fuel consumption. Specifically, it is often used to define classes of cars. In our analysis, we define luxury vehicles as those with engine displacement larger than 1.6 liter and 1.4 turbo charged.[13] The results with interactions between log hourly wage and luxury vehicle dummy are reported in column 5 of Table 8. As expected, drivers with luxury vehicles tend to have stronger reference preference.

Considering the endogeneity issue, we apply the same instrumental variables and their corresponding interactions with express drivers' dummies using 2SLS. Our estimated results are shown in the last five columns of Table 8. Overall, the results are consistent with linear regressions. For more engaged express drivers based on their online time, earned revenue, and partially mobility area, their labor supply elasticity is significantly less negative. On the other hand, amateur drivers' labor supply elasticity can be as negative as -0.523 (column 7 in Table 8), indicating the fact that they have stronger reference-dependent preferences and prone to work less during days with higher hourly wage: A percent increase in hourly wage leads to almost 0.523 percent decrease in labor supply.

[13] Generally, with a larger number of vehicle engine displacement, the vehicle is more powerful. We use 1.6 liters and the equivalent 1.4 turbo charged as the threshold because the Chinese government has halved tax policy for vehicles with vehicles powered by a small engine no larger than 1.6 liters since October 2015. We believe that it is a good indicator to define luxury vehicles. In our data, about 41% of the express vehicles are defined as luxury vehicles. Data source: http://www.xinhuanet.com/fortune/2015-10/12/c_128307844.htm (Last accessed: April 25, 2018).

Table 8. Moderating Effects of Drivers' Characteristics and Driving Patterns

	OLS					2SLS				
	(1) Time	(2) Revenue	(3) Mobility	(4) Driver pattern	(5) Car level	(6) Time	(7) Revenue	(8) Mobility	(9) Driver pattern	(10) Car level
Log hourly wage	-0.333***	-0.349***	-0.188***	-0.219***	-0.0887***	-0.200***	-0.523***	-0.521***	-0.301***	-0.218***
	(0.0208)	(0.0178)	(0.0160)	(0.0143)	(0.0143)	(0.0299)	(0.118)	(0.130)	(0.0596)	(0.0367)
Log hourly wage *engage_time	0.285***					0.366***				
	(0.0238)					(0.119)				
Log hourly wage* engage_revenue		0.328***					0.373***			
		(0.0212)					(0.131)			
Log hourly wage* engage_mobility			0.131***					0.0336		
			(0.0206)					(0.0517)		
Log hourly wage* Pattern driver				0.226***					0.184***	
				(0.0198)					(0.0638)	
Log hourly wage* Car_level					-0.0507**					-0.0284
					(0.0209)					(0.0617)
Log_age	0.0295	0.0308	0.0198	0.0184	0.0321	0.0176	0.0294	0.0291	0.0163	0.0177
	(0.0611)	(0.0607)	(0.0623)	(0.0619)	(0.0639)	(0.0622)	(0.0601)	(0.0597)	(0.0612)	(0.0620)
Low temperature	0.000349	0.000595	0.000495	0.000681	0.000637	0.000454	0.000342	0.000637	0.000652	0.000467
	(0.00107)	(0.00106)	(0.00107)	(0.00107)	(0.00108)	(0.00107)	(0.00107)	(0.00107)	(0.00107)	(0.00107)
Wind speed	0.0109***	0.0105***	0.0106***	0.0103***	0.0105***	0.0113***	0.0120***	0.0116***	0.0112***	0.0113***
	(0.00279)	(0.00278)	(0.00280)	(0.00279)	(0.00283)	(0.00283)	(0.00282)	(0.00282)	(0.00282)	(0.00283)
Visibility	-0.0124***	-0.0120***	-0.0121***	-0.0118***	-0.0121***	-0.0131***	-0.0137***	-0.0133***	-0.0129***	-0.0130***
	(0.00251)	(0.00249)	(0.00252)	(0.00251)	(0.00255)	(0.00256)	(0.00256)	(0.00254)	(0.00255)	(0.00256)
Precipitation=1	-0.0200	-0.0167	-0.0244	-0.0179	-0.0244	-0.0325**	-0.0297*	-0.0278*	-0.0280*	-0.0322**
	(0.0158)	(0.0157)	(0.0158)	(0.0158)	(0.0159)	(0.0160)	(0.0161)	(0.0159)	(0.0159)	(0.0160)
PM2.5	-0.000547	-0.000527	-0.000540	-0.000551	-0.000536	-0.000669*	-0.000747*	-0.000742*	-0.000705*	-0.000668*
	(0.000378)	(0.000376)	(0.000379)	(0.000379)	(0.000382)	(0.000381)	(0.000382)	(0.000382)	(0.000381)	(0.000381)
AQI	0.000644*	0.000615*	0.000651*	0.000646*	0.000645*	0.000788**	0.000851**	0.000840**	0.000812**	0.000787**
	(0.000371)	(0.000370)	(0.000372)	(0.000372)	(0.000376)	(0.000375)	(0.000375)	(0.000375)	(0.000374)	(0.000374)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.679***	1.590***	1.771***	1.638***	1.688***	2.072***	2.067***	2.025***	1.999***	2.063***
	(0.346)	(0.344)	(0.353)	(0.350)	(0.362)	(0.365)	(0.352)	(0.349)	(0.359)	(0.365)
Number of drivers	2,954	2,954	2,954	2,954	2,921	2,954	2,954	2,954	2,954	2,921

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

Table 9. Moderating Effects of Drivers' Characteristics and Driving Patterns: Session Data

	OLS					2SLS				
	Time	Revenue	Mobility	Driver pattern	Car level	Time	Revenue	Mobility	Driver pattern	Car level
Log hourly wage	-1.178***	-1.248***	-1.383***	-1.322***	-1.201***	-0.742***	-0.734***	-1.227***	-1.076***	-0.955***
	(0.0271)	(0.0273)	(0.0189)	(0.0194)	(0.0180)	(0.0943)	(0.0961)	(0.0761)	(0.0689)	(0.0670)
Log hourly wage *engage_time	-0.0434					0.190*				
	(0.0314)					(0.115)				
Log hourly wage *engage_revenue		0.0412					0.223*			
		(0.0316)					(0.117)			
Log hourly wage *engage_mobility			0.306***					0.264**		
			(0.0265)					(0.106)		
Log hourly wage *Pattern driver				0.190***					0.0461	
				(0.0273)					(0.102)	
Log hourly wage *Car_level					-0.0381					-0.306***
					(0.0287)					(0.106)
Log_age	-0.0321	-0.0307	-0.0355	-0.0286	-0.0242	0.00128	0.00351	-0.0286	-0.0230	-0.0151
	(0.0812)	(0.0813)	(0.0805)	(0.0813)	(0.0821)	(0.0825)	(0.0825)	(0.0804)	(0.0810)	(0.0814)
Low temperature	-0.00359***	-0.00363***	-0.00356***	-0.00363***	-0.00376***	-0.00212	-0.00205	-0.00323**	-0.00321**	-0.00336***
	(0.00125)	(0.00125)	(0.00124)	(0.00124)	(0.00125)	(0.00133)	(0.00134)	(0.00126)	(0.00126)	(0.00127)
Wind speed	0.0264***	0.0265***	0.0268***	0.0264***	0.0270***	0.0181***	0.0176***	0.0249***	0.0242***	0.0251***
	(0.00342)	(0.00342)	(0.00341)	(0.00341)	(0.00344)	(0.00366)	(0.00367)	(0.00349)	(0.00349)	(0.00352)
Visibility	-0.0305***	-0.0306***	-0.0309***	-0.0303***	-0.0309***	-0.0217***	-0.0211***	-0.0289***	-0.0281***	-0.0287***
	(0.00311)	(0.00311)	(0.00310)	(0.00311)	(0.00313)	(0.00335)	(0.00336)	(0.00319)	(0.00321)	(0.00323)
Precipitation=1	-0.0575***	-0.0570***	-0.0565***	-0.0564***	-0.0584***	-0.0318	-0.0303	-0.0514**	-0.0507**	-0.0542**
	(0.0211)	(0.0211)	(0.0211)	(0.0211)	(0.0212)	(0.0220)	(0.0220)	(0.0212)	(0.0212)	(0.0214)
PM2.5	-0.00290***	-0.00290***	-0.00283***	-0.00283***	-0.00294***	-0.00252***	-0.00251***	-0.00276***	-0.00278***	-0.00288***
	(0.000486)	(0.000486)	(0.000483)	(0.000486)	(0.000489)	(0.000516)	(0.000518)	(0.000486)	(0.000491)	(0.000491)
AQI	0.00318***	0.00318***	0.00311***	0.00311***	0.00323***	0.00273***	0.00271***	0.00302***	0.00304***	0.00315***
	(0.000476)	(0.000476)	(0.000474)	(0.000476)	(0.000480)	(0.000506)	(0.000508)	(0.000477)	(0.000482)	(0.000481)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.401***	5.390***	5.395***	5.322***	5.365***	3.070***	2.934***	4.905***	4.779***	4.801***
	(0.461)	(0.461)	(0.456)	(0.461)	(0.466)	(0.513)	(0.513)	(0.482)	(0.491)	(0.492)
Number of drivers	2,954	2,954	2,954	2,954	2,921	2,954	2,954	2,954	2,954	2,921

Clustered Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

Table 10. Moderating Effects of Drivers' Characteristics and Driving Patterns: Choice to End a Session

	Conditional Logit					Survival				
	Time	Revenue	Mobility	Driver pattern	Car level	Time	Revenue	Mobility	Driver pattern	Car level
Log cumulative online time	0.518***	0.517***	0.517***	0.515***	0.494***					
	(0.0110)	(0.0123)	(0.0106)	(0.0131)	(0.0113)					
Log hourly wage	0.145***	0.177***	0.164***	0.236***	0.113***	0.228***	0.224***	0.0971***	0.218***	0.193***
	(0.0303)	(0.0279)	(0.0215)	(0.0214)	(0.0300)	(0.0137)	(0.0138)	(0.0142)	(0.0136)	(0.0138)
Log hourly wage *engage_time	0.0480					-0.0970***				
	(0.0355)					(0.00540)				
Log hourly wage *engage_revenue		0.00351					-0.0731***			
		(0.0327)					(0.00563)			
Log hourly wage *engage_mobility			0.0282					0.0757***		
			(0.0206)					(0.00322)		
Log hourly wage *Pattern driver				-0.111***					-0.0686***	
				(0.0230)					(0.00413)	
Log hourly wage *Car_level					0.158***					0.0125***
					(0.0418)					(0.00311)
Driver's log average session time						-1.015***	-1.045***	-1.221***	-1.043***	-1.150***
						(0.0125)	(0.0128)	(0.0105)	(0.0120)	(0.0102)
Low temperature	0.00598***	0.00597***	0.00598***	0.00594***	0.00515***	0.00327**	0.00369***	0.00368***	0.00366***	0.00432***
	(0.00135)	(0.00158)	(0.00171)	(0.00160)	(0.00191)	(0.00127)	(0.00128)	(0.00128)	(0.00128)	(0.00129)
Wind speed	-0.0234***	-0.0234***	-0.0234***	-0.0233***	-0.0242***	-0.00434	-0.00520	-0.00568	-0.00589	-0.00746*
	(0.00480)	(0.00682)	(0.00555)	(0.00516)	(0.00507)	(0.00440)	(0.00441)	(0.00445)	(0.00446)	(0.00445)
Visibility	0.0367***	0.0367***	0.0367***	0.0365***	0.0363***	0.0129***	0.0136***	0.0138***	0.0142***	0.0156***
	(0.00451)	(0.00552)	(0.00474)	(0.00411)	(0.00462)	(0.00391)	(0.00392)	(0.00395)	(0.00396)	(0.00395)
Precipitation=1	0.124***	0.123***	0.123***	0.122***	0.124***	0.0476**	0.0487**	0.0433*	0.0496**	0.0550**
	(0.0247)	(0.0256)	(0.0275)	(0.0218)	(0.0244)	(0.0224)	(0.0225)	(0.0227)	(0.0226)	(0.0227)
PM2.5	0.00497***	0.00496***	0.00496***	0.00488***	0.00459***	0.00191***	0.00197***	0.00205***	0.00215***	0.00206***
	(0.000589)	(0.000714)	(0.000593)	(0.000690)	(0.000594)	(0.000603)	(0.000605)	(0.000608)	(0.000608)	(0.000610)
AQI	-0.00538***	-0.00537***	-0.00537***	-0.00529***	-0.00506***	-0.00204***	-0.00210***	-0.00215***	-0.00227***	-0.00219***
	(0.000563)	(0.000701)	(0.000577)	(0.000687)	(0.000588)	(0.000586)	(0.000588)	(0.000591)	(0.000591)	(0.000593)
Fixed effects	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Day of week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of sessions/ number of drivers	41,519	41,519	41,519	41,519	41,519	2,654	2,654	2,654	2,654	2,654

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

In Section 4.3.1, we investigate the main effect using session data. Here, we explore how drivers with different characteristics have distinct labor elasticities with session data using both linear regressions and 2SLS. The corresponding results are shown in Table 9. Interestingly, when considering the potential endogeneity issue, all the coefficients of the interactions have the expected signs. Except that of the driver pattern interaction, all other coefficients are statistically significant. These estimators provide evidence that our results are quite robust.

In Section 4.3.2, we estimate a driver's decision to continue or stop driving after a trip within a session. Here, we also add interactions between drivers' engagement, driving pattern, and car level dummies in this model to see heterogeneous effects. The corresponding results can be found in Table 10. Most of the interactions have significant and expected signs.

4.5 Drivers with Enough Number of Orders

In the dataset, a small portion of drivers only used the app for a few times during the one-month period. These drivers may have different motivations to participate in this platform. In fact, the platform has different promotions over time to encourage new drivers. For example, there was ¥10,000 reward for drivers who bought a specific car after they have accepted 10 orders in December 2015.[14] These drivers who were attracted by "new-driver" promotion may behave differently. Similarly, some of the drivers in our dataset may just join in the platform and do not have a lot of experience. They may need some time to "learn" the market and form their own strategy. Hence, in order to avoid the impact of these drivers' behavior, we conduct another robustness check with a subset of the express drivers. Specifically, we exclude the drivers whose number of orders are less than 5 percentiles in our data set, which is 32 orders.

The results are reported below in Table 11. We can see all of the results are qualitatively equivalent to those with full sample. In terms of the magnitudes of estimated labor supply elasticities, we find them to be less negative. This echoes our main result that less engaged drivers are more likely to have reference-

[14] Data source: http://www.didiabc.com/reward/155.html (last accessed: January 24, 2018).

dependent preferences. After we have removed the least engaged drivers' data, we would expect the remaining less engaged drivers to show less negative labor supply elasticities.

Table 11. Analysis with Subsample of Drivers

	OLS	2SLS			
	Main result	Main result	Time	Revenue	Mobility
Log hourly wage	-0.150***	-0.0861***	-0.188***	-0.195***	-0.148***
	(0.00660)	(0.0107)	(0.0185)	(0.0158)	(0.0151)
Log hourly wage *engage_time			0.163***		
			(0.0222)		
Log hourly wage * engage_revenue				0.201***	
				(0.0208)	
Log hourly wage* engage_mobility					0.116***
					(0.0210)
Other controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes
Day of week dummies	Yes	Yes	Yes	Yes	Yes
Constant	1.774***	1.750***	1.698***	1.603***	1.747***
	(0.0750)	(0.366)	(0.361)	(0.361)	(0.363)
Number of drivers	2,089	2,089	2,089	2,089	2,089

Clustered Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

5. Managerial and Policy Implications

The prevalence of sharing economy and online labor markets has dramatically changed the landscape of traditional industries and reshaped the distribution of unused or underutilized asset through digital platforms (Sundararajan 2016, Hong and Pavlou 2017, Mayya et al. 2017, Gong et al. 2018). Our results have broad managerial and policy implications to platforms as well as policy makers. Quantifying labor supply elasticity is important for ridesharing platforms to design platform strategies (Song et al. 2018), such as price surging algorithms and driver subsidization programs. A key purpose of price surging in ridesharing market is to stimulate labor supply of drivers. However, our findings suggest that a uniform price surging to all drivers may not be effective because the overall labor supply elasticity is negative: When price surges, ridesharing drivers reach the income target sooner and are less motivated to drive. On the other hand, we also find that the labor supply elasticity varies with drivers' characteristics and driving patterns. For more experienced and patterned drivers, they tend to drive more when price surges. Because all the information about drivers' characteristics and driving patterns is available to ridesharing platforms, they can design a

personalized price surging algorithm for specific drivers based on these characteristics and more effectively incentivize drivers' labor supply.

Our research also has implications for driver subsidization programs of ridesharing platforms. Major ridesharing platforms have announced driver subsidization programs in various formats: (i) extra bonuses if a certain number of rides were completed,[15] and (ii) reduced commission fee for drivers.[16] An objective of these subsidization programs is to encourage drivers to work more by providing monetary incentives. However, according the same logic, a uniform driver subsidization program to all drivers may not be effective because of the negative labor supply elasticity. Our research suggests that a more effective approach is to provide personalized driver subsidization programs targeting more experienced and patterned drivers.

Our finding that labor supply in ridesharing markets is reference dependent has significant policy implications. Evaluations of government policy regarding tax and transfer program in ridesharing markets relies on estimates of the sensitivity of labor supply to wage rates. If labor supply is the result of optimization with reference-dependent preferences, policy implications could be quite different. More specifically, for policy makers, estimating labor supply elasticity is critical to understand the economic efficiency of various surge pricing algorithms in ridesharing markets. If labor supply elasticity is significantly positive, then it suggests that surge pricing algorithms can increase the efficiency of ridesharing markets. However, we find a negative labor supply elasticity, which significantly reduces the economic gains from the uniform surge pricing algorithms.

[15] See https://www.uber.com/drive/atlanta/resources/driver-partner-incentive-guarantee-faq-questions and http://www.scmp.com/tech/china-tech/article/1937640/chinas-didi-recruiting-more-driver-ride-hailing-business-through (last accessed: May 21, 2018).
[16] See https://www.caixinglobal.com/2018-01-25/didis-new-subsidies-augur-second-price-war-101202995.html (last accessed: May 21, 2018).

6. Discussion and Conclusions

Ridesharing services, such as Uber and Lyft, have substantially reshaped the traditional taxi industry by matching passengers and drivers in real time. At the same time, the flexibility on the labor supply side, which is one of the innovative ridesharing services' unique features, has significant implications. In the present study, we conduct a comprehensive empirical analysis to understand the labor supply elasticity in the new ridesharing services, the heterogeneity of labor supply elasticity, as well as a comparison of elasticities of labor supply for ridesharing and taxi drivers. Specifically, we take advantage of the accurate data of drivers' activities recorded by ridesharing mobile applications as well as policy instrumental variables to investigate their labor supply decisions. Overall, we find a negative labor supply elasticity for ridesharing drivers and a positive association between the likelihood of quitting markets for ridesharing drivers and the income already earned, which suggest behavioral income-targeting model based on the theory of reference-dependent preferences to be a better explanation for ridesharing drivers' daily labor supply decisions. In addition, we explore the heterogeneity in drivers' labor supply elasticities among drivers with different characteristics and driving patterns. Our empirical results indicate that labor supply elasticity is less negative for more experienced, engaged, and regular ridesharing drivers. Last but not least, we also show some empirical evidence that taxi drivers are less influenced by the reference-dependent preferences with data from the same period and city. Our paper makes significant contributions to both the literature and industry. A better understanding of drivers' labor supply decisions helps the platform design price surging and driver subsidization programs. At the same time, our research should be of interest to policy makers investigating into this issue.

Our paper has several limitations. First of all, although the data in this study is novel and from one of the major ridesharing providers, we only have a random sample of drivers from one city during one month. Another caveat is that we do not have each vehicle's license plate information, and we predict the last digit number of each driver's license plate by analyzing the trip data. This may result in some measurement errors for the 2SLS estimators. Third, we could not observe how drivers' preferences evolve

over time. Right now, our empirical results show that drivers who are more engaged in the platform tend to be less influenced by reference-dependent preferences. It would be interesting to further investigate how drivers' preferences evolve over time if we can observe drivers' activities for a longer time period.

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