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Model and analysis of labor supply for ride-sharing platforms in the presence of sample self-selection and endogeneity

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A B S T R A C T

With the popularization of ride-sharing services, drivers working as freelancers on ride-sharing platforms can design their schedules flexibly. They make daily decisions regarding whether to participate in work, and if so, how many hours to work. Factors such as hourly income rate affect both the participation decision and working-hour decision, and evaluation of the impacts of hourly income rate on labor supply becomes important. In this paper, we propose an econometric framework with closed-form measures to estimate both the participation elasticity (i.e., extensive margin elasticity) and working-hour elasticity (i.e., intensive margin elasticity) of labor supply. We model the sample self-selection bias of labor force participation and endogeneity of income rate and show that failure to control for sample self-selection and endogeneity leads to biased estimates. Taking advantage of a natural experiment with exogenous shocks on a ride-sharing platform, we identify the driver incentive called "income multiplier" as exogenous shock and an instrumental variable. We empirically analyze the impacts of hourly income rates on labor supply along both extensive and intensive margins. We find that both the participation elasticity and working-hour elasticity of labor supply are positive and significant in the dataset of this ride-sharing platform. Interestingly, in the presence of driver heterogeneity, we also find that in general participation elasticity decreases along both the extensive and intensive margins, and working-hour elasticity decreases along the intensive margin.

1. Introduction

With the rapid development and popularization of mobile and wireless communication technologies, ride-sharing platforms such as Didi Chuxing and Uber, which use mobile wireless technology to connect passengers and drivers, are disruptively changing the transportation industry. In the traditional taxi business, drivers are normally required to obtain an occupational license, or "medallion," in order to provide transport service to passengers. The number of taxi drivers is limited by the number of medallions issued, the regions in which drivers can pick up passengers are restricted to the jurisdiction that issued medallion, and fares are often set by regulatory bodies (Cramer and Krueger, 2016). In ride-sharing markets, drivers working as freelancers can design their schedules more flexibly, which implies that they can use their own or leased cars

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to offer transport service whenever and wherever they choose. As ride requests arrive, the platforms match these requests with nearby drivers and adjust fares dynamically when demand is high relative to the supply of drivers in a local region. A driver's income depends on his/her working time and location, other drivers' supply, and passenger demand (Chen et al., 2017). Because drivers are autonomous, they are able to adjust labor supply in response to income fluctuations.

Ride-sharing platforms lean heavily on payments to boost driver income in the presence of flexible labor supply, so evaluation of the impacts of income rate on labor supply becomes important. For example, Uber offers a driver $500 for completing 120 trips in a week or a guaranteed income of $1800 for the first 200 trips. More recently, Uber's new incentive, "Boost," multiplies the driver's trip fare by a certain amount for all trips within a specified hotspot during specified times[1]. On the driver side, incentive payments may represent between 20% and 40% of a typical driver's income, according to an analysis conducted by Los Angeles-based Uber driver Harry Campbell, who runs the popular blog The Rideshare Guy. On the platform side, driver incentive payments were one of Uber's biggest operational expenses for the six quarters that ended in the first half of 2017 (Bensinger, 2017).

Motivation. Investigating the effect of hourly income rates on labor supply for ride-sharing platforms is challenging. As suggested by standard labor economics theory, income rates exert two distinct effects on labor supply by influencing two margins: one is intensive, and relates to the number of hours worked; the other is extensive, and relates to the decision to participate or not in the labor market (Cahuc et al., 2014). For nearly 20 years, labor economists have been debating on how cabdrivers decide how long to work (Scheiber, 2016). Colin Camerer, a behavioral economist, finds a negative relationship between hours supplied of New York City cabdrivers and transitory changes in wages, and argues that drivers come into the market with an income target and quit working once they reach that target (Camerer et al., 1997). In contrast, Henry Farber finds that taxi drivers tend to respond positively to increases in earnings opportunities and the estimated elasticities are generally positive (Farber, 2015). From the perspective of research design for observational studies, the endogeneity problem could bias estimation of the effect. On one hand, drivers on ride-sharing platforms face a two-step decision: Whether to participate in work, and if so, how many hours to work. However, only historical data for participating drivers is available, which indicates that data on working hours is censored. Since unobservable factors affect both the participation decision and working-hour decision, fitting on the nonrandomly selected samples would lead to *sample selection bias* (Heckman, 1979)[2]. On the other hand, drivers' working hours are not determined right after obtaining fixed income rates, because the hours worked affect the income rates. This *simultaneity bias* creates an endogeneity problem in model identification. Moreover, extensive empirical works have sought to analyze labor supply using observed hourly income rates calculated by dividing total daily income by total hours worked, which introduces *measurement error*. This will induce a negative correlation between calculated hourly income rates and hours worked.

Research questions. Motivated by these challenges in evaluating the impacts of income rate on labor supply on ride-sharing platforms, we seek to answer the following research questions: (i) Methodologically, how can we analyze the influence of income rates on overall labor supply while controlling for sample self-selection, endogeneity of the income rate, and measurement error in working hours? (ii) What is the importance of income-targeting behavior to overall labor supply as a function of daily participation and daily hours worked? (iii) How would this influence be affected by driver heterogeneity?

Methodology. To answer these questions, we first discuss a labor supply model with decisions on daily hours worked on the basis of the reference-dependent preference theory, which predicts the sign of the intensive margin elasticity of labor supply. Next, we propose an econometric approach to estimate the impact of income rates on daily labor supply response on both the extensive and intensive margins, which can accommodate both sample selection of labor force participation and endogeneity of income rate. In particular, we use an instrumental variable approach to address potential omitted variable bias and simultaneity bias issues. Finally, our empirical framework is applied to data from Didi Chuxing, which is the leading ride-sharing platform in China. Importantly, we take advantage of the driver "income multiplier" as the exogenous shock in a large-scale natural experiment to help us avoid the endogeneity problem in model identification. After classifying drivers by their extensive and intensive margins of labor supply, we present the participation elasticity and working-hour elasticity in the presence of driver heterogeneity.

Results. Our empirical analysis of labor supply reveals two key findings. First, using the dataset from a ride-sharing platform, we find that participation elasticity ranges from 0.107 to 0.524, and working-hour elasticity ranges from 0.023 to 1.037; both estimates are positive and significantly different from zero. The results do not completely exclude the possible existence of drivers income-targeting behavior. They imply that, when the average driver makes daily labor supply decision with the practical income levels in our dataset, the behavior forces in favor of neoclassical intertemporal substitution outweigh the forces that work based on income targets. Second, in the presence of driver heterogeneity, we find that in general participation elasticity decreases along both the extensive and intensive margins, and working-hour elasticity decreases along the intensive margin. Our results also reveal that labor supply elasticity is affected by driver gender and age.

Main contributions. The main contributions of this paper can be summarized as follows:

- We propose an econometric framework with closed-form measures to estimate participation elasticity (i.e., extensive margin elasticity) and working-hour elasticity (i.e., intensive margin elasticity) of labor supply. We estimate the effects of income rates on total labor supply on ride-sharing platforms and use a framework that models the sample self-selection

[1] https://www.uber.com/en-AU/drive/resources/boost/.

[2] In this paper, we use "sample selection bias" and "sample self-selection bias" interchangeably.

bias of labor force participation and simultaneity bias of working hours. We believe that the proposed framework can also be applied to analyze the labor supply of other on-demand platforms with independent agents.
- We build a natural experiment environment in which the platform implements adjustment of driver incentive as exogenous shocks. The incentive which is referred to as “income multiplier” in this paper multiplies drivers’ trip fare by a certain amount for all trips during specified times in a day. In our identification approach, the exogenous income multiplier is adopted as an instrumental variable to address the simultaneity bias problem.
- We provide empirical evidence on labor supply elasticity on ride-sharing platforms, which is positive in all groups of drivers in the data of this ride-sharing platform. Our work also highlights the importance of driver heterogeneity to the impacts of income rates on labor supply for ride-sharing platforms. Participation elasticity decreases along both the extensive and intensive margins; working-hour elasticity decreases along the intensive margin.

The remainder of the paper is as follows. In Section 2, we discuss the related literature. In Section 3, we introduce a model of drivers’ labor supply based on the reference-dependent theory. In Section 4, we propose the methodology to model drivers’ self-selection of participation and treatment endogeneity of working hours, and present closed-form expressions to estimate participation elasticity and working-hour elasticity. In Section 5, we describe our dataset and introduce the natural experiment. In Section 6, we present estimation results for labor supply elasticity in different groups of drivers. Finally, in Section 7, we summarize our main insights and discuss directions for future research.

2. Related literature

Our work connects two strands of previous research. The first is the empirical analysis of daily labor supply of workers who can decide whether to participate or choose the number of hours they work flexibly. Table 1 summarizes prior studies on the following six aspects: labor markets where both income levels and the quantity of labor supplied are varied each day, labor supply responses along both extensive and intensive margins, theoretical background, data sources, identification approaches to address endogeneity issues, and estimates of labor supply elasticities. Three important differences distinguish our research from these early studies. First, based on a large dataset from a ride-sharing platform, we conduct a complete analysis of drivers’ labor supply responses to changes in income opportunities, including responses in daily working hours and responses in number of days worked (daily participation margin). Second, we propose a *causal inference* method to control for sample self-selection bias due to participation decision and endogeneity of daily hours worked. Closest to our paper, Stafford (2015) estimates income elasticities of participation and daily working hours using a framework that deals with sample self-selection bias and endogeneity of income rates, where the moon phase is used as an instrument for hourly income rates of commercial trap fishermen in the two-stage least squares (2SLS) in order to remove bias due to endogeneity of the wage. In our work, we take advantage of a natural experiment to create exogenous shocks, and instrument the endogenous hourly income rates of drivers with the driver incentive income multiplier that is uncorrelated with measurement error. Third, taking drivers’ heterogeneity into consideration, we present the labor supply elasticities for diverse types of drivers. Comparison of elasticity estimates across different groups provides additional implications of labor supply behavior on a ride-sharing platform.

Another strand is staffing and pricing for shared transportation platforms. Representative works include (Cachon et al., 2017; Taylor, 2018; Bai et al., 2018). These papers focus on agents’ rational decisions without considering reference-dependent preferences. Zha et al. (2017) propose equilibrium models to characterize the labor supply (i.e., working hours) of drivers. Because of competing theories regarding how a driver determines his/her working hours, they present equilibrium models with neoclassical or income-targeting hypotheses. Our empirical analysis using data from the largest ride-sharing platform in China provides evidence that when the average driver makes daily labor supply decision on ride-sharing platforms, the behavior forces in favor of neoclassical intertemporal substitution outweigh the forces that work based on income targets. Similar conclusions are also reached in Fehr and Goette (2007), Stafford (2015) and Giné et al. (2017).

3. The labor supply model

3.1. Optimal decisions on hours worked with income targeting

This section introduces a theoretical model of drivers’ labor supply based on income targets. We consider their decisions of hours worked on a given day (also see Crawford and Meng, 2011; Farber, 2015; Zha et al., 2017). According to the reference-dependent preference model proposed by Kőszegi and Rabin (2006) and Farber (2015), given hourly income rate W in the platforms, a driver’s utility of working hours H (also called “hours worked” in this paper) is the sum of positive utility from his/her income earned $I = WH$ and disutility from hours worked that day. Suppose that a driver sets a daily *income target* T; then his/her utility function can be specified as follows:

$$U(I,H) = \begin{cases} (1+\alpha)(I-T) - \dfrac{\theta}{1+\eta_h} H^{1+\eta_h}, & \text{if} \quad I < T, \\ (1-\alpha)(I-T) - \dfrac{\theta}{1+\eta_h} H^{1+\eta_h}, & \text{if} \quad I \geq T, \end{cases} \tag{1}$$

Table 1
Empirical analysis of the daily labor supply of flexible workers in literature.

Labor Market	Labor Supply	Theory	Data	Identification	Elasticity
Taxicab drivers (Camerer et al., 1997)	Hours worked	Reference- dependent preference	Trip sheets of NYC cabdrivers (1988,1990,1994)	Average income as IV	Negative hours elas. (-0.355 ∼ -0.618)
Taxicab drivers (Chou, 2002)	Hours worked	Reference- dependent preference	Survey of Singapore taxi drivers	Average income as IV	Negative hours elas. (-0.3 ∼ -0.9)
Bicycle messengers (Fehr and Goette, 2007)	Hours worked, effort per hour	Reference- dependent preference	Number of shifts and revenues per shift	RCT	Negative effort elas. (-0.24), Positive hours elas. (1.34 ∼ 1.50)
Workers on the Trans-Alaska pipeline (Carrington, 1996)	Participation, hours worked	Neoclassical intertemporal labor supply	Unemployment insurance reports	Temporary demand shocks as IV	Positive participation elas. (0.738), Positive hours elas. (0.583)
Baseball stadium vendors (Oettinger, 1999)	Participation	Marginal analysis	Participation and income	Demand shifter as IV	Positive participation elas. (0.6)
Taxicab drivers (Farber, 2015)	Hours worked	Neoclassical intertemporal labor supply	Trip sheets of NYC cabdrivers (2009 ∼ 2013)	Average income as IV	Positive hours elas. (0.36 ∼ 0.62)
Commercial trap fishermen (Stafford, 2015)	Participation, hours worked	Neoclassical intertemporal labor supply	Marine Fisheries trip ticket	Moon phase as IV, selectivity correction	Positive participation elas. (0.062 ∼ 0.066), Positive hours elas. (1.05 ∼ 1.26)
South Indian boat owners (Giné et al., 2017)	Participation	Neoclassical intertemporal labor supply	Sales and loan transactions	Demand shifter as IV, selectivity correction	Positive participation elas. (0.8 ∼ 1.3), Negative participation elas. on accum. income. (-0.05 ∼ - 0.007)
Drivers in a ride-sharing firm (Sheldon, 2016)	Hours worked	Neoclassical intertemporal labor supply	Trip, hourly activity	Average income as IV	Positive hours elas. (0.13 ∼ 0.25)
Uber drivers (Angrist et al., 2017)	Participation, weekly hours worked	Neoclassical intertemporal labor supply	RCT	Incentive offer as IV	Almost zero participation elas., positive hours elas. (1.2)

(a) *Abbreviations*: IV, instrumental variable(s); RCT, randomized controlled trial; elas., elasticity; NYC, New York City; accum., (weekly) accumulated. (b) *Probability of stopping*: Farber (2005) analyzes stopping behavior of New York City cabdrivers and shows that the likelihood of quitting for the day is *positively* related to the number of hours already worked. Crawford and Meng (2011) further reconciles the finding.

where parameter $\alpha \geq 0$ represents the change in marginal utility at the income target T, $\theta \geq 0$ controls the disutility from hours worked, and $\eta_h \in \mathbb{R}$ is related to the income rate elasticity of labor supply along intensive margin. The utility with reference-dependent preferences is based on a neoclassical utility function $((I-T) - \frac{\theta}{1+\eta_h} H^{1+\eta_h})$ augmented with a gain-loss utility $\pm\alpha(I-T)$ around the reference point T. To see this, when $\alpha = 0$, $U(I, H)$ is the neoclassical utility function and the optimal working hours are

$$H_0^* = \left(\frac{W}{\theta}\right)^{\frac{1}{\eta_h}}, \tag{2}$$

which implies that the intensive margin elasticity of labor supply is $\frac{1}{\eta_h}$. Taking reference-dependent preferences into consideration ($\alpha > 0$), drivers decide their optimal working hours by maximizing the utility function in Eq. (1), which gives the following optimal solution:

$$H^* = \begin{cases} \left(\dfrac{(1+\alpha)W}{\theta}\right)^{\frac{1}{\eta_h}}, & \text{if} \quad W < \left(\frac{\theta}{1+\alpha}\right)^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}}, \\ \dfrac{T}{W}, & \text{if} \quad \left(\frac{\theta}{1+\alpha}\right)^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}} < W < \left(\frac{\theta}{1-\alpha}\right)^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}}, \\ \left(\dfrac{(1-\alpha)W}{\theta}\right)^{\frac{1}{\eta_h}}, & \text{if} \quad W > \left(\frac{\theta}{1-\alpha}\right)^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}} \end{cases} \tag{3}$$

The Eq. (3) on the optimal working hours shows that when the income rates are very low, the working hours required to achieve the income target are so high that disutility from hours worked is higher than the positive utility from income earned. Hence the optimal working hours are less than $\frac{T}{W}$ and satisfy the condition that marginal utility from consumption is equal to the marginal utility from working. For intermediate income rates, drivers choose their working hours such that their total income is equal to their target, and the range of income rates in which a driver is a target earner is $\left((\frac{\theta}{1+\alpha})^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}}, (\frac{\theta}{1-\alpha})^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}}\right)$. If α is close to zero, which implies little gain-loss utility, the range becomes very small, and the reference-dependent preference (or income target) is not important for labor supply. When income rates are sufficiently high, the working hours required to achieve the income target are so low that it is optimal to work longer ($H^* > \frac{T}{W}$).

Under the optimal working hours in Eq. (3), the intensive margin elasticity of labor supply is:

$$\eta = \begin{cases} -1, & \text{if} \quad \left(\frac{\theta}{1+\alpha}\right)^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}} < W < \left(\frac{\theta}{1-\alpha}\right)^{\frac{1}{1+\eta_h}} T^{\frac{\eta_h}{1+\eta_h}}, \\ \dfrac{1}{\eta_h}, & \text{otherwise.} \end{cases} \tag{4}$$

The reference-dependent model predicts that when income levels are intermediate, it is optimal for drivers to stop working upon reaching the income target. Under this circumstance, the income rate elasticity of labor supply at the intensive margin is close to -1; therefore, labor supply will decrease if the platform offers higher income rates to drivers.

3.2. Discussion of the labor supply model: the importance of the extensive margin

The above labor supply model with income targeting predicts the sign or magnitude of income rate elasticity at the intensive margin. However, one important motivation for our research is to understand the effects of income rates on labor supply along the extensive margin involved in drivers' participation decisions each day. Since the hourly income rate in ride-sharing markets fluctuates temporarily, both the probability of participation and daily hours worked can vary. This is because drivers increase their leisure time and non-market work when hourly income rates are relatively low, and reduce leisure and non-market work when hourly income rates are relatively high (Lucas Jr and Rapping, 1969).

From the perspective of operational practices, understanding labor supply on the extensive margin (or the number of active drivers) is relevant to the development of ride-sharing platforms. Because these platforms offer a flexible schedule with low barriers to entry, once potential drivers qualify to work on the platforms, they are free to spend as many or as few days as they like offering their transport services to passengers. A large number of drivers try ride-sharing services; some stop after a period of time, and others continue indefinitely. Taking Uber as an example, when UberX was launched, the exponential growth in the number of active Uber drivers in the United States from mid-2012 to late 2014 demonstrated that the advent of Uber had provided new opportunities to a large and growing segment of the labor force[3] In addition, predictors of the growth in the number of Uber drivers across cities, such as city population, also provide insights into the forces underlying Uber's success (Hall and Krueger, 2018).

From the perspective of market design, a two-sided matching market needs to provide thickness (Roth, 2018). Bringing a large enough number of active drivers (i.e., high extensive margin) can help make the ride-sharing market thick, which would produce satisfactory outcomes for the service, such as high matching efficiency, low proportion of unsatisfied passenger requests, and short passenger waiting time before pickup.

[3] Active drivers provided at least four trips to passengers in a given month (Hall and Krueger, 2018).

From the perspective of labor supply theory, the distinction between the extensive and intensive margins of labor supply has long been recognized in microeconometric studies (Blundell et al., 2011). The standard labor economics theory illustrates that income rates exert two distinct effects on labor supply by influencing intensive margins and extensive extensive (Cahuc et al., 2014). By splitting the labor supply behavior of drivers into participation in work and the intensity of work supplied by those participants, we can obtain a coherent picture of the impacts of hourly income rates on total labor supply. Importantly, estimates of the elasticity of labor supply based on micro data can be understated due to failure to account for the extensive margin (participation decisions) (Rogerson, 1988). Due to the important role of the extensive margin, we propose a method to model drivers' labor force participation decisions in the next section.

4. Modeling the self-selection of labor force participation and endogeneity of income rate

4.1. Methodological implications of self-selection and endogeneity

Since drivers self-select into the participation strategies appropriate to their own contexts, an empirical model that does not account for sample self-selection bias could be misspecified, and the elasticity estimates and normative conclusions drawn from such analysis could be misleading. Motivated by the income selectivity bias problem introduced by Gronau (1974), we model drivers' self-selection using the sample selection model proposed by Heckman (1976), describe drivers' two-step labor supply decision at the extensive and intensive margins, and adopt instrumental variables for the endogenous variable.

4.1.1. Modeling self-selection of labor force participation

On ride-sharing platforms, drivers face a two-step decision: (1) whether to participate in work, and (2) if so, how many hours to work. Consider a random sample of $\mathcal{I}$ drivers. Let W_{it} denote driver i's actual income rate on a given day t. Let W_{it}^0 denote driver i's reservation income rate on a given day t, which is unobservable for the platform. Let W_{it}^* denote an index of labor force attachment, which in the absence of fixed costs of work may be interpreted as the difference between income rates W_{it} and W_{it}^*, i.e., $W_{it}^* = W_{it} - W_{it}^0$ (Gronau, 1974; Heckman, 1976). According to the analysis of labor-force participation in Gronau (1974), a job hunter decides on an income rate W_{it} to distinguish between those income offers he accepts and those he rejects. Let W_{it}^0 denote the job seeker's price of time at home, he rejects an income offer that falls short of W_{it}^0. In our problem, a driver does not participate in work on days when market hourly income rate W_{it} is lower than W_{it}^0, i.e., $W_{it} \le W_{it}^0$. W_{it}^* is *unobservable*, but both driver i's participation decision $Y_{it} \in \{0,\ 1\}$ and the hours worked H_{it} on day t are *observable*. Specifically, we specify driver i's participation decision using an indicator function (i.e., 1 = "participation" and 0 = "no participation"). Then labor supply of driver i on day t can be specified by the following equations:

$$Y_{it} = \mathbb{I}\{W_{it}^* > 0\}, \tag{5}$$

$$W_{it}^* = \mathbf{X}_{1i}\boldsymbol{\beta}_1 + \epsilon_{it}, \tag{6}$$

$$H_{it} = \mathbf{X}_{2i}\boldsymbol{\beta}_2 + \varepsilon_{it}, \tag{7}$$

where $\mathbf{X}_{1i}$ and $\mathbf{X}_{2i}$ are vectors of independent variables, including hourly income rate W_{it}. $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are vectors of parameters, and ϵ_{it} and ε_{it} are error terms that capture the effects that cannot be identified or measured. We assume that $\mathbb{E}[\epsilon_{it}] = 0$ and $\mathbb{E}[\varepsilon_{it}] = 0$. The covariance of random terms for a driver i is $\mathbb{E}[\epsilon_{it}\varepsilon_{it}] = \sigma_{12}$. As a consequence of a random sampling scheme, we have $\mathbb{E}[\epsilon_{it}\varepsilon_{i't}] = 0$ for different drivers $i \neq i'$ (Heckman, 1979).

Since data for working hours H_{it} are available only if the corresponding participation decision $Y_{it} = 1$, the population regression function of the hours worked for the subsample of available data is

$$\begin{aligned}\mathbb{E}[H_{it}|\mathbf{X}_{2i}, \text{participation decision strategy}] &= \mathbf{X}_{2i}\boldsymbol{\beta}_2 + \mathbb{E}[\varepsilon_{it}|\text{participation decision strategy}] \\ &= \mathbf{X}_{2i}\boldsymbol{\beta}_2 + \mathbb{E}[\varepsilon_{it}|\mathbf{X}_{2i}, \epsilon_{it} > -\mathbf{X}_{1i}\boldsymbol{\beta}_1].\end{aligned} \tag{8}$$

If ε_{it} is independent of ϵ_{it}, which implies that the driver's participation decision and hours worked are independent, the conditional mean of ε_{it} is zero and Eq. (8) is reduced to

$$\begin{aligned}\mathbb{E}[H_{it}|\mathbf{X}_{2i}, \text{participation decision strategy}] &= \mathbf{X}_{2i}\boldsymbol{\beta}_2 + \mathbb{E}[\varepsilon_{it}|\text{participation decision strategy}] \\ &= \mathbf{X}_{2i}\boldsymbol{\beta}_2.\end{aligned} \tag{9}$$

For example, New York City cabdrivers work on almost all days due to their contracting requirements (Farber, 2015), so the participation decision strategy can be ignored and their decisions are only evidenced by the number of hours they work each day based on the income rate fluctuation. On ride-sharing platforms, drivers working as freelancers can design their schedules more flexibly, and some factors can affect both their participation decision and hours worked. For example, consider an exogenous shock that reduces a driver's price of time at home (e.g., a negative shock to household employment

([Stafford, 2015](#))). Such a shock can render a driver more likely to participate and more likely to work longer hours for any given hourly income rate. Therefore, the conditional mean of ε_{it} is nonzero and the regression estimates for parameters in Eq. (7) fit on the nonrandomly selected samples. Omitting the conditional mean as a regressor will lead to the problem of *sample selection bias*.

To address this sample self-selection problem, we construct a Heckman sample selection model to correct selection bias (Heckman, 1976; Cameron and Trivedi, 2005). Assume that ϵ_{it} and ε_{it} follow a bivariate normal distribution $\mathcal{N}(0, 0, \sigma_{\epsilon}^2, \sigma_{\varepsilon}^2, \rho)$. In practice, labor force attachment W_{it}^* is unobservable, but the parameters of the probability that a driver chooses to participate can be estimated by using probit analysis for the full sample. The specification of a probit model to describe the participation decision becomes:

$$\mathbb{P}\Big[Y_{it} = 1 | \mathbf{X}_i\Big] = \Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1), \tag{10}$$

where the standard deviation σ_{ϵ} of ϵ_{it} is normalized to be 1, and Φ and ϕ are the cumulative density function and probability density function of the standard normal distribution, respectively.

Let H_{itj} represent the working hours of driver i on day t corresponding to the participation decision j, where $j = 1$ represents the driver's decision to participate and $j = 0$ represents the driver's decision to not participate. Accounting for the nonzero covariances arising out of unobserved factors that affect both the participation (i.e., selection) and hours worked (i.e., outcome) equations above, the expected working hours of drivers that participate in work can be respecified as

$$\mathbb{E}[H_{it1} | j = 1] = \mathbf{X}_{2i}\boldsymbol{\beta}_{21} + \rho\sigma_{\varepsilon}\frac{\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)}{\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)}. \tag{11}$$

Similarly, the expected working hours of drivers that choose not to participate can be respecified as

$$\mathbb{E}[H_{it0} | j = 0] = \mathbf{X}_{2i}\boldsymbol{\beta}_{20} - \rho\sigma_{\varepsilon}\frac{\phi(\mathbf{X}_i\boldsymbol{\alpha})}{1 - \Phi(\mathbf{X}_i\boldsymbol{\alpha})}. \tag{12}$$

These two equations state that the expected hours worked are structured as the sum of two components: The first component, called *common features*, represents the effects of independent variables that influence the length of time worked, with different coefficients for drivers participating on the platform and drivers that do not participate. The second component, called *heterogeneous features*, which differs in the two equations, represents the influence of the expected value of the error terms ε_{it1} and ε_{it0} given the truncation in ϵ_{it}. The truncated density of the error term ϵ_i owing to the selection is known as the inverse Mills ratio, which is calculated from the Selection Equation as $\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)/\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)$ for drivers that participate and as $\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)/(1 - \Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1))$ for drivers that do not participate. The inverse Mills ratio terms capture the role of unobserved contextual factors that affect both the participation decision and working hours, given the self-selection into a participation decision. $\rho \neq 0$ indicates the presence of endogeneity and $\rho = 0$ indicates that the participation decision is exogenous and independent of working hours.

Outcome Eq. (11) for drivers that choose to participate implies that when drivers are randomly assigned to the participation option, the average working hours are $\mathbf{X}_{2i}\boldsymbol{\beta}_{21}$. However, when drivers self-select themselves into the participation option, the average working hours are given by $\mathbf{X}_{2i}\boldsymbol{\beta}_{21} + \rho\sigma_{\varepsilon}\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)/\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)$. If $\rho\sigma_{\varepsilon}\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1)/\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1) > 0$, we have $\mathbb{E}[H_{it1} | j = 1] > \mathbf{X}_{2i}\boldsymbol{\beta}_{21}$, which means that the working hours of drivers that choose to participate are above average working hours. In this case, the presence of unobserved characteristics will not only influence selection into the participation option, but also enable working hours to be above average.

Outcome Eq. (12) for drivers choosing nonparticipation suggests that when drivers are randomly assigned to the participation option, the average working hours are $\mathbf{X}_{2i}\boldsymbol{\beta}_{20}$. However, when drivers self-select into the nonparticipation option, the average working hours are given by $\mathbf{X}_{2i}\boldsymbol{\beta}_{20} - \rho\sigma_{\varepsilon}\phi(\mathbf{X}_i\boldsymbol{\alpha})/(1 - \Phi(\mathbf{X}_i\boldsymbol{\alpha}))$. When $\rho\sigma_{\varepsilon}\phi(\mathbf{X}_i\boldsymbol{\alpha})/(1 - \Phi(\mathbf{X}_i\boldsymbol{\alpha})) > 0$, we have $\mathbb{E}[H_{it0} | j = 0] < \mathbf{X}_{2i}\boldsymbol{\beta}_{20}$, which suggests that the presence of unobserved characteristics will then enable working hours of nonparticipants to be below average if they had worked.

4.1.2. Modeling the endogeneity of income rate

The total service time supplied by each driver on each day depends on both the participation decision and the choice of working hours. Meanwhile, the hourly income rate is also determined by the aggregate service time supplied by all participating drivers, which indicates a reverse causality between working hours and hourly income rate. Since both supply and demand curves shift from time to time, any simple regression of working hours on hourly income rate will not yield a consistent estimate of the labor supply pattern in general. In addition, while we can use our historical dataset to adjust for heterogeneous driver characteristics in our model, it is possible there are unobservable factors that influence both the income rates and labor supply, which can also lead to biased inferences when ignoring this potential source of endogeneity.

Obtaining consistent estimates requires instrumental variable-type estimation. An instrumental variable (IV) approach aims to purify the independent variable by stripping out the nonstochastic element. In principle, an IV should predict the endogenous variable of interest but is uncorrelated with the dependent variable. While IV can be effective at removing endogeneity bias, problems can arise if the IV is not strongly correlated with the endogenous variable. If an instrument is weak, the confidence intervals formed using the asymptotic distribution for two-stage least squares may be misleading, and IV estimates can be biased in the same way OLS estimates are biased (Bound et al., 1995). Additionally, IV estimates based on weak instruments are highly sensitive to small violations of the exclusion restriction (Small and Rosenbaum, 2008).

Valid IVs usually come from natural experiments or exogenous shocks. In our problem, to instrument the endogenous variable *hourly income rate*, we exploit the fact that some income adjustments could be suitable IVs because they are exogenously related to the *hourly income rate* and unrelated to the hours worked. In addition, exogenous demand shifters, such as the number of potential passenger requests, could also be used as instruments for observed hourly income rate. We will discuss the specific choice of IVs in our setting in Section 5.

Given valid IVs, a two-stage least squares (2SLS) regression analysis can be applied to jointly estimate the endogenous *hourly income rate* with its instruments and all other control variables (*Stage* 1), and the main dependent variable *hours worked* with the purified independent variable and all other control variables (*Stage* 2) (Durbin, 1954). Consider the following linear regression model with the endogenous regressor *hourly income rate*:

$$H_{it} = \mathbf{X}_{2i}\boldsymbol{\beta}_2 + W_{it}\beta_{2w} + \varepsilon_{it}, \tag{13}$$

where W_{it} is correlated with ε_{it} and this correlation generates the endogeneity problem. Let Z_t be an IV (or IVs as a vector) and γ_t its parameter. Z_t is uncorrelated with ε_{it}, i.e., $Cov(Z_t, \varepsilon_{it}) = 0$. In the first stage of the estimation procedure, the instrument equation is

$$W_{it} = \mathbf{X}_{2i}\boldsymbol{\beta}_3 + Z_t\gamma_t + \nu_t, \tag{14}$$

where ν_t is a random error term. In the second stage, the predicted values $\hat{W}_{it}$ of W_{it} are plugged into Eq. (13), and we obtain the causal regression model

$$H_{it} = \mathbf{X}_{2i}\boldsymbol{\beta}_2 + \hat{W}_{it}\beta_{2w} + \varepsilon_{it}. \tag{15}$$

Eq. (15) implies that the only reason for the relationship between hourly income rate W_{it} and IV Z_t is the first-stage instrument equation, while the instrument (vector) has no effect on hours worked other than through the first-stage channel.

4.2. Model of labor supply elasticity on a ride-sharing platform

Drivers' working decisions on a ride-sharing platform include not only whether to participate, but also how many hours to work on a given day. By Eqs. (5)–(7), let random variables Y and H be a driver's participation decision and hours worked, respectively. The total labor supply S of a driver is:

$$\begin{aligned} S &= \mathbb{E}[Y \times H] \\ &= \mathbb{P}[Y = 1]\mathbb{E}[Y \times H|Y = 1] + \mathbb{P}[Y = 0]\mathbb{E}[Y \times H|Y = 0], \end{aligned} \tag{16}$$

where $\mathbb{P}[Y = 0]\mathbb{E}[Y \times H|Y = 0] = 0$. Eq. (16) shows that the total number of hours worked of each driver can be decomposed into an extensive component $\mathbb{P}[Y = 1]$ and an intensive component $\mathbb{E}[Y \times H|Y = 1]$, where the extensive margin of labor supply is defined as the days that the driver chooses to participate (this decomposition has also been used in Blundell et al. (2013).)

Let W denote the income rate. The aggregate income elasticity of total labor supply can be defined as

$$\begin{aligned} \eta &= \frac{\partial S/S}{\partial W/W} \\ &= \frac{\partial \mathbb{P}[Y = 1]/\mathbb{P}[Y = 1]}{\partial W/W} + \frac{\partial \mathbb{E}[H|Y = 1]/\mathbb{E}[H|Y = 1]}{\partial W/W}. \end{aligned} \tag{17}$$

This equation shows that the aggregate income elasticity of total labor supply is the sum of *extensive margin* (participation) elasticity and *intensive margin* (hours worked) elasticity. To consider the two-step decisions of drivers and measure the two parts of hourly income elasticity, following the tradition of measuring labor supply elasticity from coefficients in estimated log income rate equations, we focus on the "log" version of Eqs. (10)–(12), i.e., we use $\log H_{it}$ instead of H_{it}, and $\log W_{it}$ instead of W_{it}. Then the regression models are specified as follows:

$$\mathbb{P}\Big[Y_{it} = 1|\mathbf{X}_i\Big] = \Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\log W_{it}), \tag{18}$$

$$\mathbb{E}[\log H_{it1}|j = 1] = \mathbf{X}_{2i}\boldsymbol{\beta}_{21} + \beta_{2w1}\log W_{it} + \rho\sigma_\varepsilon \frac{\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\log W_{it})}{\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\log W_{it})}. \tag{19}$$

$$\mathbb{E}[\log H_{it0}|j = 0] = \mathbf{X}_{2i}\boldsymbol{\beta}_{20} + \beta_{2w0}\log W_{it} - \rho\sigma_\varepsilon \frac{\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\log W_{it})}{1 - \Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\log W_{it})}. \tag{20}$$

Based on the equations above, elasticity at the extensive margin η_p is measured as[4]:

$$\eta_p := \frac{\partial \mathbb{P}[Y = 1]/\mathbb{P}[Y = 1]}{\partial W/W} = \beta_{1w}\frac{\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\log W_{it})}{\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\log W_{it})}. \tag{21}$$

[4] In the study of labor supply on Uber's platform, Chen and Sheldon (2016) measure labor supply elasticity using an IV model without considering extensive margin (participation) elasticity. Due to sample self-selection bias, when the two random terms are correlated, their estimated labor supply elasticity on the intensive margin will be biased.

Elasticity at the intensive margin η_{h1}, given that drivers choose to participate, is measured as:

$$\eta_{h1} = \beta_{2w1} - \beta_{1w}\rho\sigma_\varepsilon \frac{(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}{\Phi^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})} - \beta_{1w}\rho\sigma_\varepsilon \frac{\phi^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}{\Phi^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}. \tag{22}$$

Elasticity at the intensive margin η_{h0}, given that drivers choose to not participate, is measured as:

$$\eta_{h0} = \beta_{2w0} + \beta_{1w}\rho\sigma_\varepsilon \frac{(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})\overline{\Phi}(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}{\overline{\Phi}^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})} - \beta_{1w}\rho\sigma_\varepsilon \frac{\phi^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}{\overline{\Phi}^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}. \tag{23}$$

Based on the results above, the *aggregate elasticity* is measured as:

$$\begin{aligned}\eta &= \eta_p + \eta_{h1} \\ &= \beta_{1w}\frac{\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}{\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})} + \\ &\quad \beta_{2w1} - \beta_{1w}\rho\sigma_\varepsilon \frac{(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})\phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})\Phi(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}{\Phi^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})} \\ &\quad - \beta_{1w}\rho\sigma_\varepsilon \frac{\phi^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}{\Phi^2(\mathbf{X}_{1i}\boldsymbol{\beta}_1 + \beta_{1w}\mathrm{log}W_{it})}.\end{aligned} \tag{24}$$

Estimates of labor supply elasticity on ride-sharing platforms could be biased in the presence of sample self-selection and endogeneity. For example, since drivers make participation decision by comparing hourly income rate with their price of time at home, any shock that affects the hourly income rate and the price of time at home will induce correlation between the error terms in Eqs. (6) and (7). For this reason, if the correlation is nonzero and the income rate fluctuation significantly affects drivers' participation decision (i.e., $\rho \neq 0$ and $\beta_{1w} \neq 0$), by Eqs. (22) and (24), elasticity at the intensive margin for participating drivers would be biased if we do not address the sample self-selection problem. In addition, because hourly income rates W_{it} are calculated by dividing driver *i*'s total daily income on day *t* by total hours worked on that day H_{it}, and hours worked appears in reciprocal form on the right-hand side of Eq. (7), any measurement error in hours worked will induce a negative correlation between hours worked and hourly income rate. As a result, elasticity at the intensive margin η_{h1} would be downward biased. Finally, hourly income rates and hours worked conditional on hourly income rates may be jointly determined by the same factors. If these factors are unobserved, the coefficient β_{2w} will be biased due to simultaneity bias, which further leads to biased estimates of elasticity at the intensive margin. In the next section, we apply an instrumental variable approach based on a large-scale natural experiment to address the endogeneity of hourly income rate and reduce the influence of measurement error in hours worked.

5. Research design

5.1. Research context

The data we use are drawn from Didi Chuxing, the largest mobile transportation platform in China. The platform clocks around 30 million ride requests each day and covered 21 million registered drivers in 400 cities in China by 2018. It offers a diverse range of transportation services through one mobile app: Premier, Express, Hitch, Taxi, Chauffeur, and so on. In our study, we consider the *Express* service, in which Express drivers act as independent transportation service providers who determine their own work schedules.

We focus on Express service for several reasons. First, Express is the largest service on the platform, which enables us to collect accumulative data to study labor supply behavior on the platform. Second, Express service became the dominant ride-sharing service in China during the sample period, which separates it from other domestic platforms. Express service as an economic version of a private car-hailing service was introduced in May 2015. After one year, in August 2016, the platform acquired its biggest competitor in China. Platform competition would have little impact on the variation in labor supply during the sample period. Last but foremost, in order to control the nationwide budgets for supply cost, the headquarters central team of the platform (not the local team in the city of our dataset) adjusted the driver incentive called *income multiplier* during the sample period[5]. The adjustment is independent and exogenous of the demand and supply status in the local market.

[5] In contrast, before the data sample period and the natural experiment, the income multipliers were determined by the city local team.

5.2. A Large-scale natural experiment

5.2.1. Income multiplier

On ride-sharing platforms, various programs are offered to drivers to encourage them to drive and meet the demand. One of the most popular and effective programs is the *income multiplier* (also called *income accelerator*), which increases a driver's trip fare by a multiplier for all trips within a specified region during specified time. To be more specific, let the base fare of an order be P, the dynamic pricing factor $\alpha \geq 1$, the commission rate $\beta \in (0, 1)$, and the income multiplier $\delta \geq 1$. Then the total income for a driver from an order is

$$P(1-\beta) + P\max(\alpha - 1, \delta - 1), \tag{25}$$

where the first component is the income minus commission fee and the second component is the maximum of dynamic price and income multiplier. In practice, the platform charges its drivers around 20% in a commission fee, i.e., $\beta = 20\%$, and the fare P is normally calculated on a *base fare, cost per minute* $\times$ *time in ride, cost per kilometer* $\times$ *ride distance*, and *booking fee*, if any. All of these parameters are fixed during the sample period.

The income multiplier is reminiscent of the well-known dynamic pricing in our context, but they are quite different in the following two ways. First, the fluctuation in dynamic pricing factor α changes both price on the passenger side and income on the driver side, but the income multiplier only changes income on the driver side, and it has little influence on the number of passenger requests directly. Second, dynamic pricing factor α is contingent on the market supply-demand condition and dynamically changes in real time. However, the income multiplier δ is set in advance and then is announced to all drivers. Fig. 1 gives an example of the income multiplier on one day. There are five time windows, including the peak hours of 6:30–8:30 am and 17:00–18:30 pm.

5.2.2. Exogenous shocks in natural experiments

During our sample period from March 13, to May 21, 2017, in order to control the nationwide budgets for supply cost, the headquarters central team of the platform adjusted drivers' income rate using income multipliers. They did this by increasing or decreasing δ, which is independent and exogenous of the demand and supply status in the local market, and no local information has been considered to differentiate the adjustment of income multiplier in different cities. During the

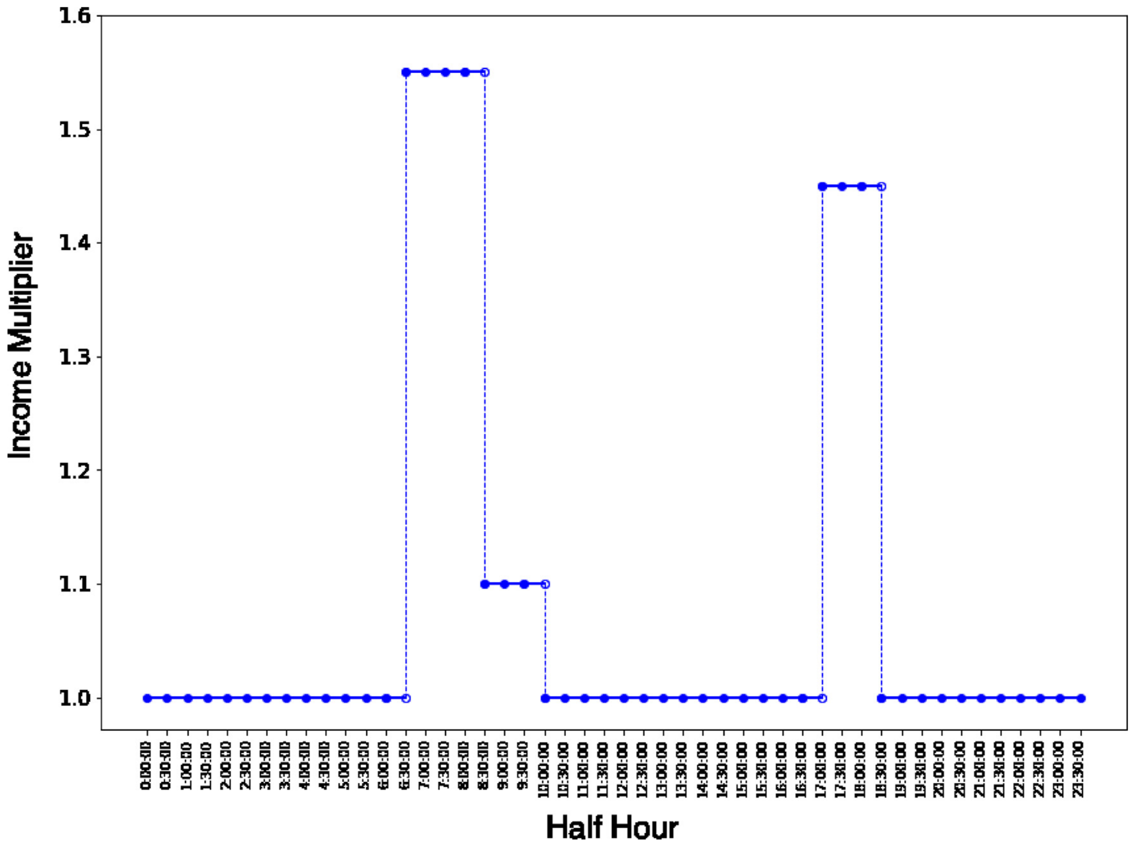

Fig. 1. An Example of an income multiplier.

sample period in our dataset, the maximal value of the variable *income_multiplier* is 1.55, the minimal value is 1.1, and the standard deviation is 0.10, which shows good interday variations of the variable *income_multiplier*.

This policy change creates natural experiments that allow us to assess how changes in income rates affect labor supply along both the extensive and intensive margins of drivers. Adjustment of income multipliers was offered only to drivers, and thus it had little direct impact on passenger demand. In addition, the adjustment was subject to *nationwide* budget controls and independent of *local* market condition. All new income multipliers each day were shared in advance with drivers in the morning. The income multiplier affected drivers' labor supply only by changing their income rates, and this exogenous shock helps us reduce bias due to the endogeneity problem in the analysis of labor supply.

5.3. Data description

5.3.1. Variable description

Our research design allows us to study the impacts of income rate changes on labor supply in the presence of driver heterogeneity.[6] The temporal unit in our analysis is a "day," but conceptualization of a driver's workday is challenging. Because drivers on ride-sharing platforms can design their work schedules flexibly due to the lack of organizational constraints on time, drivers' labor supply decision needs not resemble a typical workday from 12:00 am to 11:59 pm. For example, in informal conversations with drivers, we asked how drivers decided when to begin their shift or workday. Some said they would start working at 7:00 am and stop at 8:00 pm, and others said that they would start at 15:00 pm and stop at 04:00 am the next day to avoid fierce competition in the morning and earn more in the evening. Therefore, an approach that analyzes drivers' working hours per calendar day would split a "workday" that crosses over midnight into two driving sessions. In our analysis, we adopt the approach proposed by Chen and Sheldon (2016) to define a shift as the cluster of all trip and online service activities that happens without a break of more than 4 h. Hence, a period of driver inactivity greater than four hours marks the beginning of a new shift in our data.[7] Next, we count the number of shifts at each time (in minute) and find that 4 am is the hour with the lowest number of shifts when drivers are on the road. Finally, considering the daily adjustment of income multipliers, we define a "day" as the collection of all time during the 24-hour period between 4:00 am one day and 3:59 am the next.

A driver's hourly income rate is defined as the ratio of total daily income to daily hours worked. The underlying assumption is that there is an hourly income rate characterizing a working day that a driver can use to make her/his decision on hours worked. Camerer et al. (1997), followed by Sheldon (2016), suggest conducting an autocorrelation analysis to test this assumption. If the autocorrelation is negative, drivers may stop working early when the hourly income rate is high, because high hourly income rates are likely to be followed by low-wage hours. This labor supply behavior due to negative autocorrelation could lead to misunderstanding that drivers were making decision with income targets (Camerer et al., 1997). Therefore, understanding the time-series properties of the hourly income rates within a day is important in understanding what drivers might infer from income rate in the current hour about income rates during the remaining of the day (Farber, 2005). We conduct an autocorrelation analysis on within-day income rate by each clock hour. The results show that the first-order autocorrelation is positive (0.602) and significantly different from zero, suggesting that when the hourly income rates are high, they will probably continue to be high in the next period, which also indicates that the within-shift hourly earnings are relatively stable (Sheldon, 2016).

To capture observed driver heterogeneity, the vector $\mathbf{X}$ of control variables includes a number of time-invariant driver-specific variables: age demographics (age_i) and *gender* ($gender_i$). In addition, to account for the learning-by-doing effect and capture driver-specific heterogeneity in experience, the vector $\mathbf{X}$ also contains work experience ($experience_{it}$), measured by the number of days between the day of qualifying to work on the platform and current day t. To capture temporal variation in preference for driving, $\mathbf{X}$ includes 6 dummies for day of week (i.e., $Monday_t = 1$ if day t is on Monday; otherwise, $Monday_t = 0$). Finally, the vector $\mathbf{X}$ includes a number of weather-related variables, such as the highest temperature ($temperature_t$), the highest precipitation within 24 hours ($intensity_t$), and PM 2.5 level as an air quality index ($pm25_t$).

5.4. Driver classification along extensive and intensive margins

Based on the evidence regarding driver heterogeneity, we present a two-dimensional scheme to classify drivers. As suggested by standard labor economics theory, income rates exert two distinct effects on labor supply by influencing two margins: one is at the intensive margin and refers to the number of hours worked; the other is at the extensive margin and refers to the decision to participate or not in the labor market (Cahuc et al., 2014). Therefore, as shown in Table 2, we classify drivers based on the total number of days worked (extensive margin) and the average daily hours worked (intensive margin) in the past 30 working days.[8]

[6] The results in this paper are made using proprietary data that cannot be released. However, we do indicate levels of significance where appropriate.

[7] Farber (2015) defines any gap between trips of more than 6 hours (more than 360 min) as marking the end of one shift and the beginning of the next.

[8] Cut-off values for classifying drivers are anonymized.

Table 2
Driver classification along extensive and intensive margins.

Percentage of observations in each Group		Working hours per day		
		High	Intermediate	Low
Working days within 30 days	High	(I) 15.919%	(IV) 20.147%	(VII) 10.649%
	Intermediate	(II) 1.592%	(V) 7.142%	(VIII) 9.855%
	Low	(III) 1.095%	(VI) 4.612%	(IX) 28.989%

5.5. Empirical analysis

5.5.1. Basic model

We first use an ordinary linear regression model (OLS) given in Eq. (26) to examine the working hours of drivers at different hourly income levels. Camerer et al. (1997) estimate the regression and interpreted $\beta_{2,1}$ as the elasticity of labor supply. They show that estimates of working-hour elasticity are strongly negative, and explain that drivers set a daily income target and quit working once they reach it.

$$\begin{aligned}&\text{OLS:}\\&\log(Working\_hours_{it}) = \beta_{2,0} + \beta_{2,1}\log(income\_rate_{it}) + \beta_{2,2}age_i + \beta_{2,3}gender_i + \beta_{2,4}experience_{it}\\&+ \beta_{2,5}temperature_t + \beta_{2,6}intensity_t + \beta_{2,7}pm25_t + \beta_{2,8}Monday_t + \beta_{2,9}Tuesday_t + \beta_{2,10}Wednesday_t\\&+ \beta_{2,11}Thursday_t + \beta_{2,12}Friday_t + \beta_{2,13}Saturday_t + \varepsilon_{it}\end{aligned} \tag{26}$$

Farber (2005) recognizes an important conceptual problem and an important econometric problem with this model. First, he points out that the OLS model relies on there being significant exogenous day-to-day variation in average income, which drives the estimate of labor supply elasticity $\beta_{2,1}$ in Eq. (26). However, his/her empirical analysis shows that there is no significant interday variation in average income and no autocorrelation in hourly income rate on a particular day. Second, Camerer et al. (1997) notice that any measurement error in $Working\_hours_{it}$ would bias the estimate of $\beta_{2,1}$ downward, so they instrument the variable $income\_rate_{it}$ with the average income rate for other drivers on the same calendar date. However, Farber (2005) suggests that there might be day-specific factors correlated with both drivers' hourly income rate and working hours conditional on the hourly income rate, and other drivers' average hourly income rate were invalid as IV to estimate the causal effect of income rates on working hours.

In the natural experiment during our sample period, the platform adjusted the income multiplier daily due to budget controls, and announced it publicly in the early morning. This created exogenous day-to-day variation in drivers' average hourly income rate and helps us identify our models, which we discuss in Section 5.5.3.

5.5.2. Considering potential sample selection bias

On ride-sharing platforms, drivers face a two-step decision: whether to participate in work, and if so, how many hours to work. As discussed in Section 4.1, if some factors can affect both the participation decision and hours worked, then OLS estimates of parameters in Eq. (26) actually fit on the nonrandomly selected samples and lead to sample self-selection bias. The appropriate econometric technique for such a scenario is to model self-selection of labor force participation as presented in Section 4.1.1. Accordingly, we add to our original Eq. (26) one more Selection Equation that describes drivers' participation choice. Our Heckman two-step model specification is:

Selection equation:

$$\begin{aligned}&\mathbb{P}\Big[Participate_{it} = 1\Big] = \Phi(\beta_{1,0} + \beta_{1,1}\log(avg\_last7\_income\_rate_{it}) + \beta_{1,2}age_i + \beta_{1,3}gender_i + \beta_{1,4}experience_{it}\\&+ \beta_{1,5}temperature_t + \beta_{1,6}intensity_t + \beta_{1,7}pm25_t\\&+ \beta_{1,8}Monday_t + \beta_{1,9}Tuesday_t + \beta_{1,10}Wednesday_t\\&+ \beta_{1,11}Thursday_t + \beta_{1,12}Friday_t + \beta_{1,13}Saturday_t)\end{aligned} \tag{27}$$

Outcome equation:

$$\begin{aligned}&\log(Working\_hours_{it}) = \beta_{2,0} + \beta_{2,1}\log(income\_rate_{it}) + \beta_{2,2}age_i + \beta_{2,3}gender_i + \beta_{2,4}experience_{it}\\&+ \beta_{2,5}temperature_t + \beta_{2,6}intensity_t + \beta_{2,7}pm25_t + \beta_{2,8}Monday_t + \beta_{2,9}Tuesday_t + \beta_{2,10}Wednesday_t\\&+ \beta_{2,11}Thursday_t + \beta_{2,12}Friday_t + \beta_{2,13}Saturday_t + \varepsilon_{it}\end{aligned} \tag{28}$$

In this study, we estimate the income rate elasticities of daily participation probabilities and daily hours worked using the Heckman sample selection two-step model described in Section 4.2 that controls for self-selection bias. In the Outcome Equation, the variable $income\_rate_{it}$ is defined as the ratio of the observed total daily income that a driver i receives on a working day t to daily hours worked. In the Selection Equation, ideally, we should estimate the Probit model of participation by using the same variable $income\_rate_{it}$, however, driver i does not receive her/his income on day t when making the participation decision, and it is also impossible to observe the variable $income\_rate_{it}$ if the driver i does not participate on day t. Therefore, we estimate the Probit model of participation by replacing the observed hourly income rates with $avg\_last7\_income\_rate_{it}$, which is defined as the average hourly income rate of driver i during her/his last seven working days that she/he participated before day t. The last seven working days may be within a week, e.g., for full-time drivers, or may fall in multiple weeks, e.g., for part-time drivers. The mean of relative difference of $avg\_last7\_income\_rate_{it}$ and $income\_rate_{it}$ is between -5% and 3% across participating drivers in the 9 driver groups and days during the sample period, which shows a good approximation of $avg\_last7\_income\_rate_{it}$ as driver's perception of hourly income rate.

5.5.3. Identification of the outcome equation

In Selection Eq. (27), drivers' participation decision "happens" after the realization of average income rates during the last seven working days. However, in Outcome Eq. (28), drivers' working hours are not determined right after obtaining fixed income rates, because working hours also have effects on income rates. This simultaneity bias creates an endogeneity problem in model identification. Moreover, we analyze labor supply using observed hourly income rates calculated by dividing total daily income by total hours worked. Hence any measurement error in hours worked will induce a negative correlation between hours worked and hourly income rate. As a result, elasticity at the intensive margin would be downward biased. To address the measurement error in hours worked and endogeneity issue between hourly income rate and working hours, we adopt the IV 2SLS approach as our identification strategy, as introduced in Section 4.1.2. A valid instrument should satisfy relevance and exclusion restriction assumptions: (1) it should be correlated with the endogenous regressor (i.e., relevance condition); (2) it should be uncorrelated with the error term (i.e., exclusion restriction condition) and influence the outcome (i.e., hours worked) only through the endogenous variable (i.e., hourly income rate).

We propose two types of instruments. First, we employ the exogenous shock created by the natural experiments in our study period by creating the variable $income\_multiplier_t$. Given that the income multiplier is time-varying, we use the daily income multiplier that affects the greatest number of drivers as IV, which is the multiplier during evening peak hours 17:00–18:29 pm on day t. First, the multipliers during morning peak hours 7:00–8:29 am and during evening peak hours 17:00–18:29 pm are equal in most days and their difference is always less than 0.1 in the dataset; Second, we find that the proportions of working hours for drivers during 17:00–18:29 pm are very similar for all 9 driver groups (e.g., 13.74–16.59%). In addition, the standard deviation of hours worked during peak hours is small for each driver group (e.g., 0.86–1.60), which indicates the relative homogeneity among drivers within each group. Therefore, although the treatment effect of the income multiplier on drivers labor supply is heterogeneous for each individual, we focus on the average effect for each group. By the total income Eq. (25) for a driver from an order, variable $income\_multiplier_t$ reflects the impact of exogenous driver income on hours worked, satisfying the relevance condition. Admittedly, this IV estimates the average causal effect of treatment on the subpopulation of compliers. By the local average treatment effect theorem (Imbens and Angrist, 1994), the treatment effect identified is an average for those ("compliers") who can be induced to change hours worked by a change in the instrument. For those who never work during peak hours when the income multiplier incentive is offered, without any further assumption, the local average treatment effect is not informative (Angrist and Pischke, 2008).

Following Oettinger (1999), we supplement our analysis by adding another IV, the logarithm of number of passenger requests on day t (i.e., $request_t$) as one shifter of demand for driver supply. Although traditional taxi data cannot track total *potential* demand and can only record satisfied demand, the total potential demand is available on the ride-sharing platform. Note that the number of passenger requests used as IV is not the number of passengers who choose to send out requests for ride. It is the real potential demand, defined as the number of passengers who open the mobile app and indicate their origins and destinations before receiving estimation of waiting time and deciding whether to send out requests. The same instrumental variable is also used in Castillo et al. (2018) as demand shifts, where the endogenous pickup time determined in equilibrium is instrumented using the number of people who open the Uber app since market outcomes in no way influence whether people open the app or not, which has the same logic as our model. Although drivers may be aware of the demand peaks and surging prices during some specific hours within a day, it is difficult for them to predict the total passenger requests and income levels in a new day. Also, the temporal patterns of demand within a day could be similar across days, hence the awareness of the patterns of peak/non-peak hours within a day cannot help drivers to gain much valuable information on the income level in a new day. In this paper, we do not study the within-day working hour shifts for drivers. The number of passenger requests affects the working decisions of drivers, through the channel of affecting the hourly income rate. These two instrumental variables, $income\_multiplier_t$ and $request_t$, are correlated with hourly income rate but are not directly correlated with the measurement of hours worked, which also helps us reduce the influence of measurement error in hours worked. With the two IVs, we employ the 2SLS estimation procedure introduced in Section 4.1.2 and further provide relevant statistical tests to show that these instrumental variables are valid in Section 6.1.

6. Results and discussion

In this section, we discuss our results and summarize important findings. We show that both sample selection bias and endogeneity bias exist, which indicates that some unobservable factors indeed affect drivers' choices regarding participation and hours worked. Considering that the impact of hourly income rate on labor supply varies across different groups of drivers, we also include driver-specific fixed effects to further control for driver heterogeneity.

Table 3
Estimation results for group I (Drivers with high extensive margin and high intensive margin).

Variables	(1) OLS	(2) Heckman model without IVs		(3) Heckman model with IVs		(4) Outcome equation with fixed effects
		Selection equation	Outcome equation	Selection equation	Outcome equation	
(Intercept)	1.467***	−0.785***	1.276***	2.854***	1.696***	
log(income_rate)	0.204***		0.217***		0.152***	0.111***
log(avg_last7_income_rate)		0.326***		0.310***		
log (request)				−0.699***		
income_multiplier				−0.514***		
age	0.002***	0.012***	0.003***	0.012***	0.002***	0.001***
gender	0.008*	0.078***	0.018***	0.078***	0.007.	0.002
experience	−0.000***	−0.000**	−0.000***	−0.000**	−0.000*	−0.000.
temperature	−0.001***	−0.002***	−0.001***	0.000	−0.001***	−0.001***
intensity	−0.015***	0.060***	−0.009*	0.190***	−0.017***	−0.012***
pm25	−0.000***	−0.001***	−0.000***	−0.001***	−0.000***	−0.000***
Monday	0.001	0.007	0.002	−0.119***	−0.002	−0.003
Tuesday	−0.007**	0.033***	−0.003	−0.093***	−0.011***	−0.012***
Wednesday	0.011***	0.164***	0.030***	−0.001	0.001	0.002
Thursday	0.013***	0.198***	0.035***	0.043***	0.002	0.004
Friday	0.023***	0.210***	0.045***	0.208***	0.014***	0.019***
Saturday	0.022***	0.108***	0.034***	0.192***	0.019***	0.022***
invMillsRatio			0.259***		−0.092***	−0.046**
Weak instruments (*p-value*)					$< 2e-16$***	
Wu-Hausman (*p-value*)					$< 2e-16$***	

(a). Significant at 0.1;* significant at 0.05;** significant at 0.01;*** significant at 0.001.

In Section 6.1, we compare the estimation results of OLS, the Heckman two-step sample selection model without IVs, and the Heckman two-step sample selection model with IVs in Section 6.1.1. These results shed light on the sample selection bias and endogeneity bias. Next, we evaluate the validity of two instrumental variables by conducting statistical tests in Section 6.1.2. In Section 6.2, based on the framework proposed in Section 4, we present and discuss the estimation results of labor supply elasticity along both the extensive and intensive margins. In Section 6.3, we present estimation results by age and gender.

6.1. Model estimation

6.1.1. Evidence of sample selection and endogeneity bias

As discussed in Section 4.2, we estimate driver participation and hours worked jointly while accounting for sample self-selection bias and endogeneity. Taking Group I and Group IX as examples, Tables 3 and 4 summarize the results of different model specifications. First, we estimate OLS Eq. (26) without accounting for the sample self-selection and endogeneity, which is similar to the OLS specification in Camerer et al. (1997) using observed hourly income rate directly. The results of OLS show that the coefficients of variable $log(income\_rate)$ are positive and significantly different from zero. Second, we estimate the Heckman two-step model without IVs considering sample self-selection bias using Selection Eq. (27) and Outcome Eq. (28). The estimation results of Heckman model without IVs show that the coefficients of $log(avg\_last7\_income\_rate)$ in the Selection Equation are positive, which implies that participation probability increases as the income rate increases. The coefficients of the selectivity-corrected $log(income\_rate)$ in Outcome Eq. (28) are also positive, which is consistent with the neoclassical labor supply model. More importantly, the coefficients of the inverse Mills ratio *invMillsRatio* are significantly different from zero, which implies the existence of sample selection bias. Third, taking the endogeneity of the hourly income rates into consideration, we build on Heckman Model without IVs and control the bias by instrumenting *income_rate* using *income_multiplier* and *request*. The estimation results of Heckman model with IVs show that both the coefficients of the hourly income rates $log(avg\_last7\_income\_rate)$ in the Selection Equation and the coefficients of the selectivity-corrected $log(income\_rate)$ in the Outcome Equation are positive and significant. More importantly, we find evidence for endogeneity of the hourly income rates $income\_rate_{it}$ (the results of Wu-Hausman test are significantly different from zero at the significance level $\alpha = 0.05$), thus reject the null hypothesis that the treatment variable is exogenous with respect to hours worked. Again, the coefficients of the inverse Mills ratio *invMillsRatio* are significantly different from zero, which confirms the existence of sample selection bias. In addition, the coefficients of the inverse Mills ratio *invMillsRatio* are significantly negative, therefore, by Eq. (11), the working hours of drivers that choose to participate are less than average working hours. If sample selection bias is not taken into consideration, working-hour elasticity at the intensive margin, given that drivers choose to participate, would be biased. Finally, we include driver-specific fixed effects to control for all time-invariant aspects of each driver and day-specific fixed effects to control for all individual-invariant aspects F_{it} in Outcome Eq. (28). The estimation results of Outcome Equation with fixed effects show that the inclusion of individual and daily fixed effects does not change our estimates significantly, which ensures the robustness of our results.

Table 4
Estimation results for group IX (Drivers with low extensive margin and low intensive margin).

Variables	(1) OLS	(2) Heckman model without IVs		(3) Heckman model with IVs		(4) Outcome equation with fixed effects
		Selection equation	Outcome equation	Selection equation	Outcome equation	
(Intercept)	0.319***	−2.458***	1.531***	−2.300***	0.247	
log(income_rate)	0.163***		0.137***		0.367**	0.512*
log(avg_last7_income_rate)		0.260***		0.260***		
log (request)				0.037		
income_multiplier				−0.244***		
age	−0.000	0.003***	−0.001.	0.003***	−0.001	−0.000
gender	0.042	0.045*	0.018	0.045*	0.022	0.011
experience	−0.000***	−0.000***	−0.000**	−0.000***	−0.000***	−0.000
temperature	−0.004***	−0.003***	−0.003*	−0.003***	−0.004**	−0.006*
intensity	0.006	0.074**	−0.027	0.080***	−0.014	−0.046
pm25	−0.000*	−0.000	−0.000.	−0.000	−0.000.	−0.000
Monday	−0.016	−0.028*	−0.008	−0.041**	0.003	0.062
Tuesday	−0.029	0.012	−0.036	0.001	−0.019	0.005
Wednesday	−0.007	−0.004	−0.007	−0.011	0.020	0.058
Thursday	−0.005	−0.011	−0.000	−0.021	0.016	0.060
Friday	−0.025	0.079***	−0.058*	0.061***	−0.044.	−0.056
Saturday	0.011	0.065***	−0.016	0.072***	−0.010	−0.010
invMillsRatio			−0.549***		−0.281.	−0.358
Weak instruments (*p-value*)					$< 2e-16$***	
Wu-Hausman (*p-value*)					0.045*	

(a). Significant at 0.1;* significant at 0.05;** significant at 0.01;*** significant at 0.001.

6.1.2. Validity of instrumental variables

To evaluate the validity of the instruments (i.e., *income_multiplier* and *request*) and ensure asymptotic consistency of IV estimators, we check both the relevance condition and the exclusion restriction condition. In terms of the relevance condition, in order to know whether the instruments (i.e., *income_multiplier* and *request*) explain a sufficient amount of variation in *income_rate*, we perform a weak identification test by encompassing an F-test for the joint significance of the first-stage regression, yielding the *F*-statistics of 1934 for Group I and 70.62 for Group IX with an extremely low *p*-value. These F-statistics are well above the suggested rule of thumb for weak instruments (Staiger and Stock, 1997), indicating that our IVs combined are not weak and should satisfy the relevance condition.

To further evaluate the validity of the instrument variables and check the exclusion restriction condition, we conduct a set of Hausman tests as introduced in Guevara (2018). Specifically, one model is estimated using the two instruments (*income_multiplier* and *request*), and two models are estimated using only one instrument (*income_multiplier* or *request*). Under the null hypothesis, both instruments are exogenous and the estimators are consistent, and therefore generate similar results; the estimator $\hat{\boldsymbol{\beta}}_2$ obtained from the model using two instruments are more efficient because it makes use of more information (Guevara, 2018). Under the alternative hypothesis, if one of the two instrumental variables is endogenous, the estimator $\hat{\boldsymbol{\beta}}_2$ will be different from the estimator $\hat{\boldsymbol{\beta}}_1$ obtained from the model using only one instrumental variable. The statistic S_{HAU} of the HAU test is distributed Chi-square with degree 1 and is defined as

$$S_{HAU} = (\hat{\boldsymbol{\beta}}_1 - \hat{\boldsymbol{\beta}}_2)'(\Sigma_{\hat{\boldsymbol{\beta}}_1} - \Sigma_{\hat{\boldsymbol{\beta}}_2})^{-1}(\hat{\boldsymbol{\beta}}_1 - \hat{\boldsymbol{\beta}}_2) \sim \chi^2_{df}, \tag{29}$$

where $\Sigma_{\hat{\boldsymbol{\beta}}_2}$ is the variance-covariance matrix of the estimators of the efficient model (the one using two instrumental variables), and $\Sigma_{\hat{\boldsymbol{\beta}}_1}$ is the one obtained using only one instrumental variable. Take Group I as an example, comparing results in Tables 3 and 5, we find that $\hat{\boldsymbol{\beta}}_2$ and two $\hat{\boldsymbol{\beta}}_1$ are similar. In the Probit Selection Equation, the coefficient estimator of the variable *log*(*avg_last*7*_income_rate*) is 0.310, 0.312, and 0.324, respectively. In the Outcome Equation, the coefficient estimator of the variable *log*(*income_rate*) is 0.152, 0.156, and 0.119, respectively. In addition, the results of Hausman test for Group I is shown in the last row in Table 5. The *p*-values of the HAU test are 1, which means that we do not reject the null hypothesis of the validity of the two instrumental variables. Similar results can be found for all other driver groups at a significance level $\alpha = 0.01$, which provide evidence to support the exogeneity of these instruments.

6.2. Estimates of labor supply elasticity in the presence of driver heterogeneity

Based on the estimates of Outcome Equation with fixed effects, we summarize labor supply elasticities along both the extensive and intensive margins in Table 6. Due to sample selection bias, elasticity η_{h1} for participating drivers is different from elasticity η_{h0} for non-participating drivers at the intensive margin. Interestingly, participation elasticity η_p at the extensive margin, which ranges from 0.107 to 0.524, decreases along both the extensive (e.g., Group I $<$ Group II $<$ Group III) and intensive margins (e.g., Group I $<$ Group IV $<$ Group VII); working-hour elasticity for participating drivers at the intensive margin η_{h1}, which ranges from 0.023 to 1.037, decreases along the intensive margin (e.g., Group I $<$ Group IV $<$

Table 5
Estimation results of alternative model specification for group I (Drivers with high extensive margin and high intensive margin).

Variables	Heckman model with *request* as an IV		Heckman model with *income_multiplier* as an IV	
	Selection equation	Outcome equation	Selection equation	Outcome equation
(Intercept)	2.206***	1.667***	−0.100	1.884***
log(income_rate)		0.156***		0.119***
log(avg_last7_income_rate)	0.312***		0.324***	
log (request)	−0.703***			
income_multiplier			−0.529***	
Age	0.012***	0.002***	0.012***	0.001***
Gender	0.079***	0.007*	0.077***	0.003
Experience	−0.000**	−0.000*	−0.000**	−0.000
Temperature	0.001	−0.001***	−0.003***	−0.000*
Intensity	0.162***	−0.016***	0.088***	−0.019***
pm25	−0.001***	−0.000***	−0.001***	−0.000
Monday	−0.083***	−0.001	−0.030***	−0.004.
Tuesday	−0.062***	−0.011***	−0.000	−0.015***
Wednesday	0.028***	0.003	0.134***	−0.012**
Thursday	0.078***	0.005.	0.161***	−0.011**
Friday	0.242***	0.017***	0.176***	0.002
Saturday	0.167***	0.020***	0.134***	0.013***
invMillsRatio		−0.064***		−0.226***
Weak instruments (p-value)		$< 2e-16$***		$< 2e-16$***
Wu-Hausman (p-value)		$< 2e-16$***		$< 2e-16$***
HAU test (p-value)		1		1

(a). Significant at 0.1;* significant at 0.05;** significant at 0.01;*** significant at 0.001.

Table 6
Summary of labor supply elasticities.

Group	Estimation		Supply elasticity				Aggregate elasticity
	β_{1w}	β_{2w}	η_p	η_{h1}	η_{h0}	$\lambda\eta_{h1} + (1-\lambda)\eta_{h0}$	η
I	0.310	0.111	0.107	0.117	0.122	0.118	0.224
II	0.124	0.109	0.113	0.100	0.101	0.101	0.213
III	0.238	0.066	0.206	0.023	0.034	0.029	0.229
IV	0.342	0.352	0.163	0.362	0.367	0.364	0.525
V	0.257	0.249	0.203	0.235	0.237	0.236	0.438
VI	0.185	0.248	0.225	0.195	0.226	0.216	0.420
VII	0.421	0.852	0.275	1.037	1.065	1.048	1.312
VIII	0.368	0.860	0.488	1.023	0.950	0.967	1.512
IX	0.260	0.512	0.524	0.600	0.531	0.535	1.124

(a) λ is the average percentage of drivers who choose to participate on each day.

Group VII). Finally, the aggregate elasticity η also decreases along the intensive margin (e.g., Group I $<$ Group IV $<$ Group VII).

In summary, the estimated positive income rate elasticities of labor supply show that the labor supply along both the extensive and intensive margins on the ride-sharing platform responds positively to a change in the hourly income rates in the dataset. The results do not completely exclude the possible existence of drivers' income targeting behavior. They imply that, when the average driver makes daily labor supply decision with the practical income levels in our dataset, the behavior forces in favor of neoclassical intertemporal substitution outweigh the forces that work based on income targets (also see Fehr and Goette, 2007; Stafford, 2015).

Considering that the time period (e.g., hour, day, week, month, and year) is very important in drivers' strategic and/or tactic labor supply behavior, and the definition of time scale/unit (again, hour, day, week, month, and year) in the model may affect the results, we also conduct another set of models using *week* as time unit to explore the *weekly* labor supply response that accounts both participation and working-hour decisions. The results are statistically significant and qualitatively consistent with the results obtained from the models using *day* as time unit.

6.3. Labor supply in subgroups

To further investigate the impact of hourly income rate on labor supply, we estimate labor supply elasticities in different subgroups of drivers. Table 7 summarizes estimates for male and female drivers. We find that a higher hourly income rate can significantly increase male drivers' labor supply in all groups, and the decrease in participation elasticity along both extensive and intensive margins still holds for male drivers. However, the effect of hourly income rate on hours worked for female drivers is not significant. One possible explanation is the low proportion of female drivers on the ride-sharing

Table 7
Supply elasticities of male and female drivers.

Group	Male			Female		
Elasticity	η_p	η_{h1}	η	η_p	η_{h1}	η
I	0.108***	0.118***	0.226	0.046.	0.130*	0.177
II	0.135***	0.089**	0.224	−0.469**	−0.039	−0.508
III	0.212***	0.015	0.228	0.113	0.459	0.572
IV	0.160***	0.342***	0.501	0.238***	0.307***	0.545
V	0.200***	0.306***	0.506	0.252***	−0.403	−0.151
VI	0.220***	0.184***	0.403	0.318**	0.588*	0.906
VII	0.275***	0.980***	1.255	0.262***	1.014***	1.275
VIII	0.485***	1.013***	1.498	0.562***	1.462**	2.024
IX	0.526***	0.480.	0.975	0.482***	0.716***	0.648

(a). Significant at 0.1;* significant at 0.05;** significant at 0.01;*** significant at 0.001. These are the significance levels for estimates of β_w.

Table 8
Supply elasticities of drivers in different age groups.

Group	Youth			Middle-aged			Senior		
Elasticity	η_p	η_{h1}	η	η_p	η_{h1}	η	η_p	η_{h1}	η
I	0.101***	0.056**	0.157	0.102***	0.105***	0.207	0.109***	0.146***	0.255
II	0.127*	0.168**	0.295	0.088*	0.041	0.129	0.161*	−0.048	0.113
III	0.317***	−0.020	0.297	0.165***	−0.000	0.165	0.013	−0.065	−0.052
IV	0.180***	0.373***	0.553	0.151***	0.333***	0.484	0.159***	0.305***	0.463
V	0.145***	0.292**	0.437	0.234***	0.313***	0.547	0.215***	0.323**	0.538
VI	0.217***	0.305**	0.522	0.277***	−0.002	0.275	0.010	0.221	0.232
VII	0.259***	1.103***	1.362	0.300***	0.974***	1.274	0.225***	0.918***	1.143
VIII	0.500***	0.815***	1.315	0.481***	1.158***	1.639	0.471***	0.788***	1.259
IX	0.520***	0.533	1.054	0.525***	0.475***	1.000	0.517***	1.024***	1.335

(a). Significant at 0.1;* significant at 0.05;** significant at 0.01;*** significant at 0.001. These are the significance levels for estimates of β_w.

platform, which leads to smaller sample size in each group. Table 8 presents the labor supply elasticities of drivers in different age groups and reveals that labor supply elasticity is affected by driver age. There is also no evidence of negative elasticities in all age groups.

7. Conclusion

We evaluate the impacts of hourly income rate on daily labor supply of drivers on ride-sharing platforms. First, we propose an econometric framework to estimate the income rate elasticity of participation and working-hour, which considers the sample self-selection bias of labor force participation and the endogeneity of hourly income rate. Next, taking advantage of a natural experiment to create exogenous shocks, we empirically analyze the impacts of hourly income rate on labor supply along both the extensive and intensive margins by instrumenting endogenous hourly income rate with the driver income multiplier. We estimate both the extensive margin elasticity and the intensive margin elasticity of labor supply on a ride-sharing platform using a framework that controls for sample self-selection bias, endogeneity of the income rate, and measurement error in hours, in the context of a natural experiment. The estimated results reveal that when the average driver makes daily labor supply decision on ride-sharing platforms, the behavior forces in favor of neoclassical intertemporal substitution outweigh the forces that work based on income targets. In particular, using the dataset from the ride-sharing platform, we find that participation elasticity ranges from 0.107 to 0.524, and working-hour elasticity ranges from 0.023 to 1.037. Interestingly, in the presence of driver heterogeneity, we find that in general participation elasticity decreases along the extensive margin (number of working days) and along the intensive margin (number of working hours per day), and working-hour elasticity decreases along intensive margin.

It is important to take into account the limitations of our findings. First, although we propose a model to describe the effects of hourly income rate on labor supply, it dose not yield the optimal participation and working-hour decision for drivers. An interesting avenue for future research would be to create a theoretical model to jointly analyze decisions on daily participation and hours worked. Second, we employed instrumental variables to address the endogeneity issue of income rate, but the treatment effect identified is an average for those treated. Therefore, it would be desirable to design randomized control experiments to further evaluate the heterogeneous treatment effects of income rates on labor supply of drivers. Finally, because of data limitations, our study does not examine the impact of other factors, such as multi-homing behavior in platform competition and social interaction among drivers. These factors would be worth studying in the future.

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Supplementary material

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