The Impact of Behavioral and Economic Drivers on Gig Economy Workers

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Problem Definition: Gig economy companies benefit from labor flexibility by hiring independent workers in response to real-time demand. However, workers' flexibility in their work schedule poses a great challenge in terms of planning and committing to a service capacity. Understanding what motivates gig economy workers is thus of great importance. In collaboration with a ride-hailing platform, we study how on-demand workers make labor decisions; specifically, when to work and for how long.

Academic/Practical Relevance: Our model offers a way to reconcile competing theories of labor supply regarding the impact of financial incentives and behavioral motives on labor decisions. We are interested in both improving how to predict the behavior of gig economy workers and understanding how to design better incentives.

Methodology: Using a large comprehensive dataset, we develop an econometric model to analyze workers' labor decisions and responses to incentives while accounting for sample selection and endogeneity.

Results: We find that financial incentives have a significant positive influence on the decision to work and on the work duration—confirming the positive income elasticity posited by the standard income effect. We also find support for a behavioral theory as workers exhibit income-targeting behavior (working less when reaching an income goal) and inertia (working more after working for a longer period).

Managerial Implications: We demonstrate via numerical experiments that incentive optimization based on our insights can increase service capacity by 22% without incurring additional cost, or maintain the same capacity at a 30% lower cost. Ignoring behavioral factors could lead to understaffing by 10–17% below the optimal capacity level. Lastly, inertia could be a potential sign of workers' loyalty to the platform.

Keywords: empirical operations, behavioral operations, gig economy, incentives, sample selection, inertia

1. Introduction

Gig economy is a labor-sharing market system where workers engage in short-term projects or freelance work as opposed to permanent jobs. In 2019, 57 million Americans or 35% of the U.S. workforce engaged in gig work (Intelligence 2019), providing a wide range of services, from ride-hailing (e.g., Uber, Lyft) to food delivery (e.g., DoorDash, Caviar) to web development (e.g., Upwork, Fiverr). The size of independent workforce is growing three times faster than the overall U.S. workforce growth since 2014 and it is estimated that by 2025, the majority of the workforce will participate in the gig economy—leading to a global GDP boost of $2.7 trillion (Manyika et al. 2015). The unique and novel feature of this system relates to the nature of employment: independent workers can freely choose their work schedule as well as seamlessly switch between multiple platforms to provide service. For example, nearly 70% of ride-hailing drivers in the U.S. work for both Uber and Lyft while 25% work for more than two platforms (Campbell 2017). Such flexibility attracts many workers to the gig economy.

Companies also greatly benefit from increased labor flexibility as they can hire workers with different skill levels to work at different times while compensating them for the work they perform. Like any other market, the key to success in the gig economy lies in the effective matching of supply with demand. Firms need to ensure that their services appeal not only to customers (demand) but also to independent service providers (supply). This poses an enormous challenge in planning and committing to a service capacity both during peak hours when demand is high and during off-peak times when only a handful of workers are needed.

While companies deal with the challenges posed by such flexibility, policymakers have also joined the conversation, concerned with how such work structures might affect workers. For instance, New York City passed fatigued driving prevention rules as part of its Vision Zero initiative in 2017, limiting the number of daily and weekly hours a ride-hailing driver can work with the goal of reducing driver fatigue and enhancing road safety. In 2019, the European Parliament approved new EU rules that provide minimum rights and enforce better job transparency and compensation for gig workers.

To examine how firms can staff the right number of on-demand workers at the right time and how policymakers can develop effective regulations, it is important to first understand how gig workers make labor decisions. For decades, economists have studied how labor supply is influenced by economic incentives and behavioral motives. The standard income effect predicts that workers, as lifetime-utility maximizers, are more likely to work or supply more labor in response to a higher wage. While several observational studies find evidence for this theory (e.g., Oettinger 1999, Sheldon 2016), other studies suggest the opposite prediction. NYC taxi drivers are found to work for fewer hours on a high-paying day and more likely to quit working in response to higher accumulated income due to reference-dependent behavior with respect to earnings (e.g., Camerer et al. 1997, Thakral and Tô 2019). In other words, their decisions are based on reaching a target level of income or *income target*. Providing further support for the behavioral theory of labor supply, Crawford and Meng (2011) and Farber (2015) suggest that workers' behavior could perhaps be influenced by a target level of work duration or *time target*.

Our paper aims, in part, to reconcile this ongoing debate by proposing a framework to explain labor decisions through both economic incentives and behavioral motivations. Recent work in operations management in the context of the gig economy has focused on the system equilibrium or the total social welfare (e.g., Kabra et al. 2017, Ibrahim 2018, Taylor 2018). To our knowledge, among the papers that focus on the supply side (e.g., Benjaafar et al. 2019, Gurvich et al. 2019, Dong and Ibrahim 2020), our work is the first to empirically examine the causal effect of behavioral and economic factors on gig economy workers' decisions and to incorporate their behavior into the optimization of financial incentives.

Research questions and methodology. Our key research questions are: (i) *How do gig economy workers make labor decisions?* How do they react to incentives? What are the factors that shape their work schedule decisions? Are their decisions rational or do they exhibit behavioral biases? and (ii) *How can gig companies set incentives to effectively recruit workers?* How can they meet the desired service level by taking into account workers' behavior and offering the right incentives?

We answer these questions by estimating an econometric model of workers' labor decisions and conducting numerical experiments on incentive optimization. Prior empirical studies on the relationship between wage and labor decisions have not distinguished between the decision of whether to work and the work duration decision and instead treated them essentially as a single decision due to data limitations. Through our collaboration with a U.S. ride-hailing company, we overcome this challenge by leveraging our rich dataset which contains real-time information on financial incentives regardless of drivers' subsequent labor decisions. Accordingly, we gain a clearer insight into drivers' decisions to work by investigating drivers who chose not to work during a particular period. In our empirical model, we address econometric challenges such as sample selection and omitted variable biases, and account for drivers' heterogeneity and real-time market conditions and competition. Finally, we propose an optimization heuristic for incentives and conduct counterfactual simulations to examine its performance and to quantify potential losses if the company ignores workers' behavior when designing incentives.

Contributions. Our paper contributes to the economics and operations literatures in four ways. First, we offer a potential way to reconcile the two competing theories of labor supply by showing that workers respond to wage variation in the same way as suggested by the standard income effect, while also exhibiting reference-dependent behavior with respect to accumulated earnings. We find that an hourly wage has a positive impact on both the decision to work and the work duration. However, our proxy for unobserved income targets—accumulated earnings from earlier hours of the same day or earlier days of the week—has a negative impact on both decisions. This finding provides support for an income-targeting behavior; that is, workers work less as they are closer to their income goal. Second, we unravel a new behavioral driver of labor decisions, *inertia*. Our results indicate that workers' recent work duration (from earlier hours of the same day or earlier days of the same week) has a consistent and positive influence on the decision to continue working and on subsequent work duration. This phenomenon appears to capture the tendency of workers or inertia to make the same work decision as their recent ones. Furthermore, it can potentially hint at workers' loyalty to the focal platform. Third, we demonstrate that behavioral factors play an important role in workers' labor decisions. Both in-sample and out-of-sample analyses suggest that workers' reaction to accumulated earnings and past work duration are key drivers of their labor decisions. We then demonstrate via simulations that not accounting for these behavioral factors would result in understaffing by 10–17%. Finally, we apply our insights to prescribe operational decisions and conduct regulatory impact analysis. Specifically, we show that if the company optimizes their incentive policy accounting for workers' behavior, it can increase the capacity by 22% without incurring additional cost or maintain the same service level at a 30% lower cost. We then demonstrate that understanding how workers make decisions can inform policymakers to improve worker welfare through effective regulations.

2. Labor Supply Theories and Hypotheses Development

Economists have offered two different perspectives centered around the elasticity of labor supply. The traditional approach follows a lifecycle model where individuals maximize their lifetime utility and predicts that workers exhibit positive income elasticity. On the other hand, empirical studies, notably in the context of taxi drivers, suggest that income elasticity could be negative if workers are loss averse and benchmark their earnings relative to a reference point. It is unclear whether existing findings can apply to gig economy workers who have full discretion over their work schedule. In this section, we review in greater detail the two contrasting models of labor supply and develop hypotheses for the behavior of gig economy workers.

2.1. Traditional Model of Labor Supply

In the neoclassical microeconomics tradition, each worker is a rational agent who maximizes lifetime utility. A positive wage shock should then lead to a larger group of workers joining the force or to a higher level of activity from workers. In other words, workers are expected to exhibit a positive wage elasticity, e.g., work more when facing a wage increase. This perspective seems plausible but finding evidence in the field has been challenging as in reality workers cannot easily adjust their work hours. However, positive elasticities have been observed among workers who have some level of discretion over their schedule, such as pipeline workers (Carrington 1996), vendors in a baseball stadium (Oettinger 1999) and fishermen (Stafford 2015). These studies find that wage shocks, typically driven by temporary demand variation, have a positive effect on labor supply—both on the number of workers and work hours.

2.2. Behavioral Model of Labor Supply

The seminal work by Camerer et al. (1997) studies NYC taxi drivers and finds substantial negative elasticities, suggesting that drivers' daily decisions on work hours are influenced by their individual income targets (known as the *income-targeting* effect). Using data from a different set of NYC taxi drivers, Farber (2005) and Farber (2008) find that the probability to stop working is closely related to the realized income earned in the same day and it increases once the income target is reached, but conclude that the findings are not robust. Crawford and Meng (2011) implements similar econometric strategies to estimate models based on the reference-dependent preferences theory, which allows for consumption and gain-loss utilities. The authors conceptualize drivers' targeted levels of income and work hours and find that stopping probabilities are more influenced by the second target they reach on a given day. More recently, Thakral and Tô (2019) estimates a structural model of labor supply of NYC taxi drivers, allowing a time-dependent relationship between earnings and the stopping probability. Their results confirm that the income-targeting effect exists when controlling for the number of work hours. These findings offer a realistic behavioral explanation and align well with insights from behavioral economics; however, support for the behavioral theory has been lacking outside the taxi industry. Note that none of the previous work attempted to model both the decision to work and the work duration, as we do in this paper.

2.3. Labor Supply in the Gig Economy

The gig economy offers workers a flexible part-time work schedule. Some workers fully rely on gig work as a primary source of income, while others keep their full-time job and earn additional income via the gig economy. As gig work appeals to a broad range of workers with different backgrounds and preferences, predicting the turnout or service capacity at any point in time is remarkably challenging. A common way to incentivize new workers to join and to keep existing workers active on the platform is to offer financial incentives. New Lyft drivers earn a one-time sign-on bonus when joining and receive a weekly guaranteed earning rate for the first few weeks of driving (e.g., $1,000 weekly guarantees in the first four weeks for Los Angeles drivers). Real-time bonuses, such as Uber's surge prices and Caviar's Peak Pay, reward workers who work during busy periods with high demand. Beyond direct monetary rewards, several companies employ a combination of gamification and psychology and offer non-monetary incentive programs. Uber drivers can earn badges for achievements, from excellent service to entertaining ride, and are constantly reminded of how close they are to their earning goals. DoorDash's Dashers with high customer rating and completion rate will be added into the Top Dasher program that comes with more flexible scheduling opportunities and higher priority when matching with customers. While these incentive strategies are prevalent in practice, less is known in academic research about their influence on workers' labor decisions.

Our paper belongs to the fast-growing research trend that examines operational and pricing decisions in the context of the gig economy (see, e.g., Cachon et al. 2017, Taylor 2018, Benjaafar and Hu 2020). Most relevant to our work are studies that examine how dynamic wages affect supply and consider the problem of designing the optimal incentives to coordinate supply with demand for on-demand service platforms. Dynamic wages due to surge pricing are shown to entice ride-hailing drivers to work longer (Chen and Sheldon 2016) and benefit drivers via better utilization (Cachon et al. 2017). Hu and Zhou (2019) studies the contracts under which the platform takes a fixed cut from workers' earnings and demonstrates good performance among flat-commission contracts. Taylor (2018) shows that the uncertainty in delay-sensitive customers' valuations or in the workers' opportunity costs can lead the intermediary to raise the price during congestion. In Gurvich et al. (2019), the platform determines the cap on the number of workers allowed to work and the market-condition-contingent price and wage, and the workers decide whether or not to work after observing the market condition. The authors find that worker independence reduces the number of workers and increases the optimal price.

While there is a large body of research on flexible or self-scheduling workforce in operations management, there are relatively few studies that investigate the supply side behavior and its impact on the platform's operational decisions. Moreover, most of the studies are of a theoretical nature and focus on the equilibrium of matching supply with demand. Ibrahim (2018) examines a queueing system with a random number of servers and characterizes the optimal staffing policy and the resulting cost. Dong and Ibrahim (2020) further studies optimal staffing decisions when the workforce is composed of both contingent and permanent workers. The authors show that staffing decisions depend on the uncertainty of the flexible workers, the operating costs, and customer demand. Benjaafar et al. (2019) studies an equilibrium model of labor welfare that accounts for interactions between supply and demand and investigate the possible alignment and misalignment of the platform's and workers' interests. The authors find that labor welfare first increases with the labor pool size and then decreases.

The only empirical studies that incorporate workers' behaviors to our knowledge are Sheldon (2016), Kabra et al. (2017), and Chen et al. (2019). Sheldon (2016) finds that Uber drivers' income elasticities are positive and significant and appear to increase over time, suggesting that if income targeting exists, it would only be temporary and moderated by experience. Kabra et al. (2017) investigated the impact of incentives using data from a Singaporean taxi company. Their structural estimation results suggest that offering incentives to drivers is more effective than passengers' incentives. Chen et al. (2019) documents how Uber drivers value real-time flexibility and estimates the driver surplus from the flexible schedule. The authors find that drivers earn higher surplus from Uber's flexible model relative to less flexible arrangements.While these papers rigorously capture how drivers responded to incentives and controlled for endogeneity, their models do not consider potential behavioral factors in explaining workers' behavior. This is due to data limitations given that most datasets record trips only when they happened. In our dataset, however, we observe the information available to drivers even when they decided not to work. We focus on the behavior of gig economy workers and on how the platform can improve its operational decisions by understanding such behavior. We next present hypotheses on labor decisions of gig economy workers.

2.4. Hypotheses Development

We are interested in studying how gig economy workers make labor decisions, specifically whether they will work at a particular time and, if so, for how long. Labor decisions typically depend on multiple factors such as weather and external commitments. Yet, these are not controlled by the platform and thus, while we attempt to control for such factors, we focus on the impact of economic drivers (hourly wage) and behavioral factors (workers' income and time targets). Several companies have exploited workers' tendency to set goals by helping workers track their progress towards the goals and nudging them to work for a longer period. Since individuals' targets cannot be observed, we use workers' accumulated earnings since the beginning of their work day as a proxy for their income target and the duration of their work so far as a proxy for their time target. We next present our hypotheses regarding the impact of each factor on gig economy workers' labor decisions.

H1: A higher wage increases the probability of working and the work duration. Following the standard income effect (see 2.1), we expect that a higher hourly wage will increase the probability of working. Empirical studies of workers who have discretion over their work hours suggest that workers adjust labor decisions in the same direction as wage (see, e.g., Oettinger 1999, Stafford 2015). We posit that gig workers also exhibit a positive income elasticity as they have full control over their schedule. Unlike traditional employment, gig work tends be smaller and temporary projects (e.g., assembling furniture, driving within a city) that require less time to complete. Consequently, work decisions are made more frequently and for a shorter time frame. The objective is therefore likely to maximize utility (e.g., earnings) in the following period. We still believe that there exists a behavioral explanation of labor supply, but such effect would be driven by accumulated earnings and/or work hours instead (see H2 and H3 below). Past studies providing support for an income targeting effect only modeled the relationship between the number of work hours and the average daily wage. We postulate that the negative impact on work duration will only be apparent during specific times of day (days of week), when workers might be closer to reaching their daily (weekly) income targets. Thus, when controlling for both accumulated income and work hours separately, we should observe a positive income elasticity.

H2: Higher accumulated earnings so far decreases the probability of working and the work duration. Studies of taxi drivers including Camerer et al. (1997), Farber (2008), and Thakral and Tô (2019) provide support for an income-targeting behavior; that is, the probability to stop working increases once the income target is reached. Thakral and Tô (2019) further demonstrates that drivers' decisions are highly influenced by recent earnings. Gig workers are also likely to be influenced by the income-targeting effect, as tracking their progress towards the income goal is much easier. Several gig platforms provide real-time information about workers' recent work activities and earnings through their apps, and also provide frequent feedback about their earnings (e.g., after every completed trip for ride-hailing drivers). An alternative explanation of the negative impact of accumulated income is related to fatigue. Specifically, higher accumulated earnings could indicate a greater level of effort. Consequently, workers who experienced more fatigue would work for a shorter time. As a result, we expect to see a negative impact of the accumulated earnings on both the probability of working and on the work duration.

H3: Longer time worked so far decreases the probability of working and the work duration. Previous work in labor economics suggests another type of a targeting behavior: time targeting. Crawford and Meng (2011) develops a structural stopping estimation model that allows for reference points in both daily income and work duration among taxi drivers and concludes that drivers are loss averse relative to both reference points. Agarwal et al. (2015) and Farber (2015) find that the probability of ending a work shift is positively related to cumulative work hours. As introduced in H2, fatigue could also be explained by work duration. Recent findings suggest that work performance deteriorates toward the end of long shifts among paramedics (Brachet et al. 2012) and part-time call center agents (Collewet and Sauermann 2017). Thus, we expect that the longer the workers have recently worked, the less likely they would continue working and, if they do work, the work duration would be shorter compared to those with shorter past work duration.

3. Data: Ride-hailing Platform in New York City

To answer our research questions, we collaborate with an on-demand ride-hailing company (referred to as "the company" or "the platform") and analyze a large comprehensive dataset of driving activities and financial incentives in NYC over a period of 358 days (from October 2016 to September 2017). Our data includes: each driver's vehicle type, experience with the platform, number of hours driven, and financial incentives offered and earned. The key advantage of our data is that we observe the incentives that were offered to *every* driver regardless of the decision to drive. In other words, even for drivers who decided not to drive for a particular time period, we still know their offered wage and promotions for that period. In total, we have several million driver-shift observations and several thousand unique drivers.[1] We next present an overview of the platform and report descriptive statistics of working shifts, financial incentives, and vehicle types.

3.1. Platform Overview

The company is a ride-hailing online platform that offers services in several cities worldwide. The users (riders) may request rides in real-time through a smartphone application. Then, the platform will match riders with available drivers. This platform offers a sharing service (i.e., several passengers heading in the same direction may share the same vehicle). To make the service more efficient, passengers can be picked up and dropped off at an optimized location near the exact requested locations. Finally, drivers usually own larger vehicles and the vast majority are compensated according to a guaranteed hourly rate regardless of the number of completed rides (this compensation model is different from several other ride-hailing platforms). We focus on drivers who are paid by the hour as this scheme resembles the traditional wage model but with more flexibility on the drivers' side. This allows us to investigate how drivers' work decisions are influenced by variations in monetary incentives.

Figure 1 **Breakdown of shifts for each operating day**

3.2. Shifts and Work Schedule

Each operating day is divided into six shifts specified by the company (see an illustration in Figure 1): morning non-rush hours from midnight to 7am (*AM Off-peak*), morning rush hours from 7 to 9am (*AM Peak*), midday from 9am to 5pm (*Midday*), afternoon rush hours from 5 to 8pm (*PM Peak*), evening non-rush hours from 8 to 9pm (*PM Off-peak*), and late night from 9pm to midnight (*Late night*). The largest volume of activities happen during PM Off-peak, followed by PM Peak, and Midday, while AM Off-peak hours are the least busy. In our data, an average driver works 2.1 days per week and 6.35 hours per day.

In this paper, we analyze drivers' behavior at both the shift and day levels. We control for the day of the week to account for demand and supply variation. In our data, 49.46% of all completed trips occurred between Tuesday and Thursday, potentially confirming the popularity of the service among city commuters. Monday and Friday trips account for 30.91% of all trips, while weekend trips account for 19.62%. While drivers are allowed to flexibly decide their own work schedules, they often stick to their "regular" times. For example, 30.41% of drivers never worked on weekends.

[1] We cannot reveal the exact number of drivers and the size of our dataset due to confidentiality. However, these exact numbers do not affect any of our results or findings.

91.07% of drivers' working days did not overlap with midnight (e.g., they did not work overnight). We include past work patterns in our models to control for such heterogeneity among drivers.

3.3. Earnings and Incentives

Drivers receive a shift-specific hourly rate for the time they are *active* on the platform, which we refer to as *offer* in the sequel. They are considered active when they log on to the application on their mobile device and report to their designated start location. This compensation scheme can be considered as a guaranteed payment, in contrast to a commission-based contract that compensates drivers for each completed trip—commonly used by several platforms. It is possible under this scheme that drivers could be paid even if there are no ride requests for the entire hour. Similar schemes are used by other platforms such as DoorDash and HourlyBee.

The guaranteed hourly offer comprises two components: a base rate and a promotional rate. These two variables vary over time (shifts and days of week) and across different drivers. The base rate for each driver is decided when the driver joins the platform for the first time. For the same driver, the base rate may be different across shifts and across days of the week, but typically remains the same across weeks. In addition to the base rate, drivers are frequently offered promotional incentives. Rate-based promotions provide a multiplicative bonus to the hourly base rate during specific times (e.g., during $2\times$ shifts, drivers earn twice the base rate). 32.71% of shifts in the data include rate-based promotions and the average promotion rate is an additional 50.36% of the base rate or approximately $1.5\times$.

At the time of our data, incentives were decided as follows: First, the platform sets a number of promotional rates as benchmarks. Then, an algorithm uses these rates to assign the final rate for each driver based on recent work history and vehicle type. Both the base and promotional rates are specific to each driver. The platform then sends text messages to drivers every evening to communicate the rates for the following day. This suggests that drivers are likely to plan their work schedule ahead of time and there is no internal competition for better rates among drivers. Occasionally, drivers may receive real-time adjustments to their rates but will never experience lower rates than initially informed. All rates are pro-rated to the actual amount of time worked in a given shift. Earnings are cumulative until the end of the week when drivers have the option to transfer them to their bank account.

3.4. Drivers and Vehicle Types

Drivers are identified by their unique IDs. For each shift, we observe the decision to work (i.e., to become active) for every driver registered in the system. For drivers who started working after the first day of our dataset, we record both their first day joining the platform and their first work day to control for their experience with the platform. Similarly, we observe the last day of being registered with the platform for some drivers if they left within the duration of our data. These allow us to control for drivers' experience, tenure, and span of their service for the focal platform.

For the analysis conducted in this paper, we consider only the drivers who own a single vehicle (89.9% of all drivers). There are six types of vehicles: a 3-passenger sedan, a small 3-passenger SUV, a medium 4-passenger SUV, a large 5-passenger SUV, a 5-passenger van, and a 6-passenger van. We exclude van drivers from our analysis as the majority of them lease their vehicle from the company rather than owning their vehicle or leasing it from an external third party, leaving us with 86.3% of the original pool of drivers. For our main analysis, we present the results for two types of vehicles: sedan and large SUV, which are 33.2% of the pool. We make an assumption that drivers of different vehicle types may have fundamentally different utilities and preferences. Sedan vehicles are generally less expensive to maintain than SUVs, while SUV drivers may have a different set of outside opportunities (e.g., qualified for both regular and large/XL services). From our data, we observe that SUV drivers typically work more frequently and for longer hours relative to sedan drivers. We obtained similar qualitative results for other vehicle types; but omit the results for conciseness.

3.5. Supplementary Data

NYC Trip Records. We incorporate trip records for other similar services in the same region to better capture the market conditions. Trip records of taxis as well as for-hire vehicles (FHVs) have been collected by the NYC Taxi and Limousine Commission (TLC) and publicly released since 2009.[2] In particular, we analyze 101,487,565 yellow taxi trips and 129,868,077 FHV trips operated by four major service providers (including our focal platform) in the city between October 2016 and September 2017 (i.e., the duration of our main data). Yellow taxi trip records include date, time, and location (at the neighborhood level) of every pick-up and drop-off, itemized fares, and driver-reported passenger counts. FHV trip records prior to July 2017 consist of date, time, and location of each pick-up as well as the dispatching base license number associated with a ride-hailing platform. Starting from July 2017, we also observe date, time, and location of each drop-off by FHV drivers. With this data, we construct a number of metrics to control for market conditions and competition in NYC §4.1.

Weather. We retrieve weather data from the Dark Sky API, which provides minute-level weather information for a specific location (NYC in our case). This data includes humidity, precipitation probability and intensity, precipitation type (rain, snow, or sleet), temperature, apparent or "feel-like" temperature, visibility, and wind speed.

[2] https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page

4. Empirical Approach

To test the hypotheses developed in §2, we estimate the impact of financial incentives, income and time targets, and other covariates on two labor decisions: (i) *whether to work or not* and (ii) *work duration*. We assume that drivers make both decisions at the beginning of each shift/day. We conduct our analyses at two levels, within-day (*shift level*) and across-days (*day level*), as well as for each vehicle type separately. This allows us to understand how variations within the same day or across days affect drivers' decisions and to capture vehicle type-specific heterogeneity. Drivers operating different vehicle types may have different preferences, costs, and utility functions, and thus make their labor decisions differently. In this section, we first introduce our econometric model and key covariates, then provide details of our estimation method, and finally discuss the empirical challenges and our strategies to address them.

4.1. Empirical Model and Estimation Details

Our dataset provides a unique advantage as we observe the financial incentives offered to *every* driver for *every* shift as long as the driver already joined the platform and have not yet terminated their drivership. This allows us to study two stages of labor decisions and control for potential sample selection bias (see §4.2.1 for further discussion). Our approach therefore adapts the two-stage Heckman estimation method (Heckman 1979) to first estimate the decision to work across all drivers using a probit regression, and then estimate the work duration for drivers who chose to work for any given shift or day using an OLS regression.

4.1.1. Outcome variables. The decision of the first stage is captured by a binary variable $Drive_{i,t}$. Specifically, $Drive_{i,t} = 1$ if driver i works during a shift or day t and $Drive_{i,t} = 0$ otherwise. In the second stage, conditional on working during shift or day t, $Hours_{i,t}$ represents work duration in hours for driver i during t. Given the long tails in $Hours_{i,t}$, we apply a Box-Cox transformation conditional on the covariates to normalize its distribution and homogenize variance. Our results are robust under other types of transformation (e.g., logarithm, square root) and without transformation. We exclude outliers defined as drivers whose work duration during a given shift or day exceeds the 1.5 interquartile ranges (IQRs) or less than 5 minutes. We also exclude public holidays from our analysis.

4.1.2. Key covariates. We focus our analysis on three key drivers of labor decisions. *(i) Financial incentives.* We use the hourly offer rate (i.e., the sum of hourly base rate and promotions, if available), denoted as $w_{i,t}$ for driver i during shift or day t, for the first stage. Similarly, conditional on working, the second stage's financial incentives are taken from the hourly earnings rate (i.e., the sum of hourly base rate and promotions, if available), denoted as $\tilde{w}_{i,t}$. *(ii) Income targets.* As we do not directly observe drivers' income targets, we use cumulative earnings since the beginning of the day (week) until the focal decision point as a proxy for a daily (weekly) income target. We refer to this covariate as *income so far* or ISF. The rationale behind this proxy is that, as the driver starts accumulating earnings, the higher ISF, the closer they are to their privately known targets. The same proxy is used in the literature (e.g., Crawford and Meng 2011, Thakral and Tô 2019). *(iii) Time targets.* Similarly, we use cumulative work hours since the beginning of the day (week) until the focal decision point as a proxy for a daily (weekly) time target. We refer to this covariate as *hours so far* or HSF. Given our observation that over 90% of data do not include overnight work, we assume that daily targets and progress are "reset" at midnight (e.g., the driver starts working towards a new target for the new day). Similarly, as the majority of work was during weekdays, we assume that weekly targets are reset at the end of every Sunday. Our results are robust to different constructs of targets and flexible frequency of target reset.

4.1.3. Two-stage estimation. Let $w_{i,t}, \tilde{w}_{i,t}, ISF_{i,t}$, and $HSF_{i,t}$ be hourly offer, hourly earnings rate, cumulative income, and cumulative work hours of driver i at the beginning of time t, respectively. $\boldsymbol{X_{i,t}}$ and $\boldsymbol{Z_{i,t}}$ are other relevant covariates that affect the decision to work and work duration, respectively. We model the two stages of labor decisions, $Drive_{i,t}$ and $Hours_{i,t}$, of driver i at time t as follows.

$$Hour_{i,t} = \begin{cases} Hour^*_{i,t} & \text{if} \quad Drive_{i,t} = 1 \\ \text{unobserved} & \text{otherwise} \end{cases} \tag{1}$$

$$Drive_{i,t} = \begin{cases} 1 & \text{if} \quad Drive^*_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$Drive^*_{i,t} = \alpha_{0,i} + \alpha_w w_{i,t} + \alpha_{ISF} ISF_{i,t} + \alpha_{HSF} HSF_{i,t} + \boldsymbol{\alpha X_{i,t}} + v_{i,t} \tag{3}$$

$$Hour^*_{i,t} = \beta_{0,i} + \beta_{\tilde{w}} \tilde{w}_{i,t} + \beta_{ISF} ISF_{i,t} + \beta_{HSF} HSF_{i,t} + \boldsymbol{\beta Z_{i,t}} + u_{i,t} \tag{4}$$

$$\begin{bmatrix} \sigma_v^2 \\ \sigma_u^2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma_u \\ \rho\sigma_u & \sigma_u^2 \end{bmatrix} \right). \tag{5}$$

The two stages that we estimate are given by:

$$P(Drive_{i,t} = 1 | \boldsymbol{X_{i,t}}) = \Phi(\alpha_{0,i} + \alpha_w w_{i,t} + \alpha_{ISF} ISF_{i,t} + \alpha_{HSF} HSF_{i,t} + \boldsymbol{\alpha X_{i,t}}), \tag{6}$$

$$f(Hour_{i,t}) = \beta_{0,i} + \beta_{\tilde{w}} \tilde{w}_{i,t} + \beta_{ISF} ISF_{i,t} + \beta_{HSF} HSF_{i,t} + \boldsymbol{\beta Z_{i,t}} + \theta \lambda_{i,t} + u_{i,t}, \tag{7}$$

where $\Phi(\cdot)$ is the normal c.d.f. and $\lambda_{i,t}$ is the inverse Mills ratio (IMR) calculated from the predicted probability in Equation (6) (*"Choice Equation"*). Thus, we essentially estimate a probit model for the work decision in Equation (6) and compute the IMR for each observation. We then fit an OLS model of the (transformed) work duration conditional on all covariates and the IMR (Equation (7)), while controlling for the drivers who worked (*"Level Equation"*). The estimated coefficient $\theta = \rho\sigma_u$ will potentially confirm the existence of a sample selection bias. We next discuss in detail the estimation methodology for each stage.

Choice: Control function probit. The first stage is based on a probit model of labor decisions, $Drive_{i,t}$. We address a potential endogeneity related to financial incentives and past work decisions by taking an instrumental variable (IV) approach (see §4.2.2). A commonly used two-stage least squares (2SLS) can provide inconsistent estimates for a probit model as certain properties of the expectation and linear projection operators do not carry over to nonlinear models (Newey 1987). Instead, we implement the control function method to account for endogeneity for our nonlinear probability model (Imbens and Wooldridge 2007, Wooldridge 2015). The first step is identical to the first step of 2SLS, that is, we estimate an OLS regression of the endogenous variable ($w_{i,t}$) on exogenous covariates and instrumental variables. We can then keep the endogenous variable in the model and include the residuals from the previous regression as an additional regressor. The intuition behind this method relies on using the instrument to split the unmeasured confounders into two parts, one that is correlated with the endogenous regressor and one that is not. We correct for the standard errors using the standard deviation of the residuals following Imbens and Wooldridge (2007).

We also allow for drivers and time fixed effects throughout our estimation. Adding fixed effects to the nonlinear choice equation is known to generate the incidental parameters problem. More precisely, the usual asymptotic properties of the maximum likelihood estimator are not guaranteed, thus leading to a biased and inconsistent estimator (Greene 2004). Fortunately, recent developments in bias correction, such as the jackknife estimation method (see Hahn and Newey 2004, Dhaene and Jochmans 2015 for more details on this method), allow us to obtain asymptotically unbiased estimates and alleviate the incidental parameters problem. The final step for this stage is to compute the IMR for each observation using the fitted probability.

Level: Fixed effects 2SLS. The second stage aims to estimate the work duration, $Hour_{i,t}$, conditional on the driver working during the focal time period. The hourly earnings rate, $\tilde{w}_{i,t}$, is likely to be endogenous. Incorporating the IV approach to the level equation is straightforward as we can simply perform a 2SLS regression in which we first obtain the predicted value of $\tilde{w}_{i,t}$ based on exogenous covariates and the IVs. We transform the observed work duration using a Box-Cox approach conditional on all covariates to alleviate heteroskedasticity. Finally, as we include the IMR as one of the regressors in the second stage, we bootstrap the standard errors by repeating our analysis on resampled datasets.

Other covariates and model selection. To capture drivers' heterogeneity, we first include a driver-specific intercept in both stages even if we already perform separate analyses for drivers with different vehicle types. We also include other time-varying driver-specific covariates that could reflect their work habits. Short-term habits are captured by historical work duration on the same day and shift of the previous week and the total hours worked during the previous week. Long-term habits are captured by the driver's experience (i.e., whether they are new to the platform and their tenure) and also through the drivers' fixed effects. Month and day-of-week fixed effects are also included to capture seasonal trends. For model selection, we randomly split our data into 65% training, 30% testing, and 5% validation sets. The final sets of covariates are then decided based on in-sample fitting, comparing AICs through stepwise method and the mean squared errors through LASSO regression, and out-of-sample prediction performance. The final sets of regressors in our main model are:

- **Choice:** hourly offer (w), cumulative earnings (ISF), cumulative work hours (HSF), number of hours worked last week, new driver indicator, humidity, apparent temperature, precipitation probability, number of other ride-hailing trips in the previous shift/day (in thousands).
- **Level:** hourly earning rate ($\tilde{w}$), cumulative earnings (ISF), cumulative work hours (HSF), number of hours worked on the same shift of last week, humidity, apparent temperature, precipitation probability, number of other ride-hailing trips during the same shift/day (in thousands).

4.2. Empirical Challenges and Strategies

4.2.1. Sample selection bias. Previous studies such as Camerer et al. (1997) and Sheldon (2016) investigated the relationship between the number of work hours and the hourly wage conditional on drivers who worked on a given day. This would not be a concern if drivers randomly decide whether or not to work. In reality, however, it is more plausible that they make such decisions based on factors which are not observed by the researcher. In other words, the selection of drivers who choose to work at a given time is not random. Consequently, this approach may yield a biased estimate of the sensitivity to incentives (i.e., income elasticity). Fortunately, the comprehensiveness of our data offers an opportunity to address this challenge. Since we observe incentives for all drivers on every shift regardless of their work decisions, we can directly estimate the selection problem. As presented in §4.1.3, we employ a modified two-stage Heckman estimation method for our analysis.

While Heckman-type selection model has been widely used in several applications, it has also been criticized on its potential pitfalls, particularly the weak nonlinearity of the IMR and the multicollinearity of regressors in both stages (Puhani 2000). To address these concerns, we carefully choose the sets of regressors for both stages ($\boldsymbol{X_{i,t}}$ and $\boldsymbol{Z_{i,t}}$) to be different (as shown in §4.1.3) and we check for collinearity by regressing the IMR on the regressors of the second stage. On average, the standard deviation of the errors is 44.52% less than the standard deviation of the IMR, which suggests a substantial difference. We also consider an alternative approach suggested by Puhani (2000): estimating a subsample OLS or a two-part model. In the two-part model, a binary choice model is estimated for the probability of observing a positive-versus-zero outcome (e.g., the number of work hours). This is essentially the same as the first stage of our main approach. Conditional on a positive outcome (e.g., drivers who worked during a particular shift/day), a separate OLS regression model is estimated for the work duration (Cragg 1971, Madden 2008, Farewell et al. 2017). This is the same as the second stage of our main approach excluding the IMR. We report the estimates from both the two-part model and our main approach in §5. Finally, as a robustness check, we consider the Dahl's approach by using a basis spline to approximate the choice probability (Dahl 2002). For more details on the approach, we refer the reader to Bourguignon et al. (2007) that provides Monte Carlo comparisons across different selection models and to Bray et al. (2019) that implements this correction to model proximity-based supplier selection. In our context, the choice for each driver is binary. Our results remain consistent and are presented in Appendix B.1.

4.2.2. Endogeneity. As discussed in §2.1, the standard income effect suggests that financial incentives encourage workers by increasing their likelihood of working or work duration. Nevertheless, quantifying the effect of incentives by regressing the labor decision on financial incentives can lead to misleading results. In our dataset, we observe that a smaller fraction of drivers who received an hourly offer of \$65 decided to work relative to those who received \$45 per hour. One possible implication is that financial incentives are not effective in inducing some drivers. Alternatively, these appealing promotions might have been strategically offered to engage inactive drivers. Consequently, regressing work decisions on financial incentives can lead to an omitted variable bias as we do not observe the actual algorithm behind these incentives. Overlooking this issue may yield to a bias estimate of the effect of financial incentives. A common solution is to use instrumental variables (IVs) that are highly correlated with financial incentives but affect the work decision only through the incentives (Levinsohn and Petrin 2003).

Instrumental variables. The main endogenous variables in our data are the hourly financial incentives, $w_{i,t}$, and the hourly earnings, $\tilde{w}_{i,j}$. Our ideal instrument is one that is highly correlated with each endogenous variable and affects the dependent variable (the decision to drive or the work hours) only through the endogenous variable. In other words, we are looking for instruments that are not correlated with the unobserved variables in the error terms. Our industry partner confirmed that the financial incentives were endogenously determined with respect to supply decisions. Specifically, the company sets the financial incentives based on past work history, level of inactivity, and vehicle type. This insight motivated us to focus on instruments that categorize drivers based on these three factors.

Our instrument is based on the notion of *co-workers*. For each driver who is available to work at a particular time (i.e., has not terminated their partnership with the platform), we define their co-workers as the drivers who meet the following conditions: (i) available to work at the same time, (ii) drive a different vehicle type, and (iii) have made the same work decision in the past (i.e., the same shift in the previous week or previous month). Work decisions are binary such as working or not. Assuming that random shocks, $v_{i,t}$ and $u_{i,t}$, are not correlated across drivers, we propose to use the average hourly offers received by co-workers for the focal period as an IV. This IV satisfies the *relevance condition:* since both the focal driver and their co-workers made the same work decision in the past, their incentives should be highly correlated. From the first stage of our IV estimation, the estimate for the instrument is consistently significant and F-statistics for all models are larger than the conventional threshold of 10. This IV also satisfies the *exclusion restriction:* current incentives for co-workers should not directly influence the focal driver's work decision because (i) they drive different vehicle types, and (ii) the focal driver does not have access to co-workers' incentives information.

To test the robustness of our results, we consider two alternative instruments. First, instead of matching drivers based on their decision *to work* at a specific time in the past, we now match drivers based on their decision *not to work*: the level of past inactivity. For every day in our data, we categorize drivers into four groups based on each quartile of the number of consecutive days they have not been working. We refer to the drivers of a different vehicle type who belong to the same group as *co-skippers*. Finally, we also consider the instrument used in previous literature (e.g., Sheldon 2016), the average hourly offer rate received by all other drivers during the same shift on the same day as an instrument for the offer rate. We obtain consistent insights under all three specifications. Further details are deferred to Appendix B.2.

4.2.3. Multicollinearity. A potential concern of including both HSF and ISF in the same specification is the multicollinearity issue. Correlations between ISF and HSF in our data range from 0.446 to 0.929, depending on the time of the day and the vehicle type. This issue does not significantly affect our results because of three reasons. First, despite a positive correlation, HSF and ISF are not a direct transformation of each other, hence there is no perfect correlation. Intuitively, HSF increases linearly with time as it denotes the exact amount of time the driver has been working, while ISF evolves dynamically as it depends on time-varying financial incentives. Second, multicollinearity generally makes causal inference difficult as the variance of each estimate would be inflated, leading to statistical insignificance, but the estimate itself would be unbiased. Our main results (see §5) show that this is not the case for us as both coefficients for HSF and ISF are statistically significant in most cases. Third, potential problems from high collinearity can be largely offset with sufficient power (Mason and Perreault Jr 1991). Our dataset consists of a large enough number of observations to provide sufficient statistical power even when we separately estimate our model by vehicle type, day of the week, and shift of the day. Finally, we consider several alternative approaches to alleviate the multicollinearity concerns, including considering models with only ISF or HSF, performing localized regressions by controlling for drivers with similar ISF or HSF, and converting one of the two variables to be categorical. Our insights remain qualitatively consistent. Further details and discussion are deferred to Appendix B.3.

4.2.4. Competition with other ride-hailing platforms. One of the key features of the gig economy is the flexibility that gig workers have in choosing their work schedule as well as for which platform to work. During the timeframe of our dataset, there are four major ride-hailing companies operating in NYC. All ride-hailing drivers require a TLC license plate to work in the five city boroughs. Drivers on our focal platform are therefore eligible to work and could have worked for other companies and made these choices during the same time with our data. Capturing the outside options of each driver is thus crucial in understanding their labor decisions. The main challenge is that we do not observe when drivers from our focal platform could have worked for other companies nor the information about incentives outside our focal platform. In our main specification, we include two covariates that can shed some light on the current market conditions for ride-hailing services. First, we capture the recent volume of rides operated by the ride-hailing competitors using the number of trips from the TLC trip records data. In the choice equation, we include the number of trips on competing platforms initiated in the previous period, $NumFHV_{t-1}$, to reflect the market condition observed by the drivers of our platform at the time of decision t. Second, we capture the current volume of competing services in the level equation by using the number of trips initiated in the same period, $NumFHV_t$.

We create two additional metrics to capture competition effects by leveraging additional information on drop-off time and location of all FHV drivers as well as the trip distance and duration of taxi drivers (which is only available starting from July 2017). First, to capture the traffic and congestion conditions, we compute the speed (in miles per hour) for each taxi trip by dividing the trip distance by the trip duration. We then compute the average speed for trips initiated in each neighborhood at each time period. To match with a shift (or day) in our data, we average across all neighborhoods and time periods within the shift or (day). We then include the average speed, $Speed_t$, in both stages. Second, to reflect potential real-time adjustments to financial incentives (e.g., surge pricing) on competing platforms, we compare the imbalance between supply and demand in each neighborhood at each time period. We assume that drivers who recently dropped off passengers in the neighborhood reflects the number of potential supply of drivers in that neighborhood. In the same vein, if we observe a larger number of trips picking up passengers from a specific neighborhood, we can infer that this neighborhood has high demand (compared to supply), and hence would likely trigger surge prices on the competitors' platforms. We define the binary variable $Surge_{l,t}$ as whether the number of trips leaving location l is at least 1.5 times greater than the number of trips entering the same location at time t. In other words, surge pricing is likely to be activated when there are at least 50% more ride requests than the number of available drivers in the neighborhood. Using different thresholds yields qualitatively similar insights. We then compute the number of neighborhoods in the city with $Surge_{l,t} = 1$ for each time t. Aggregating across hours to a shift level, we obtain $AggSurge_s = \sum_{t \in \text{Shifts}_s} (\sum_{l \in \mathcal{L}} Surge_{l,t})/|\mathcal{L}|$ as our metric for potential real-time appealing opportunities for the drivers to work for the competing platforms during shift s, where $\mathcal{L}$ is a set of neighborhoods in NYC. Our insights remain valid under each of the above metrics. Details and discussion of the results are presented in Appendix C.

5. Empirical Results

We first present our analysis at the shift level, understanding the impact of financial incentives, income and time targets on within-day labor decisions of SUV and sedan drivers. The results for the Midday shift are discussed in detail and a summary of results for the remaining shifts is subsequently provided. We then perform the analysis at the day level, to study across-day labor decisions from Tuesday to Sunday. We discuss the insights from both analyses and test the hypotheses developed in §2. Finally, we consider several robustness checks that help validate our findings.

5.1. Within-Day Analysis

We examine drivers' labor decisions at the beginning of each of the company-specified shifts as introduced in §3.2. As 91% of drivers' working days observed in our data do not overlap with midnight and 73% of work day happened between 7 a.m. and midnight, we assume that the first possible shift of the day is AM Peak (starting at 7 a.m.) and the last possible shift of the day is Late Night (ending at midnight). Our analysis focuses on four shifts (Midday to Late Night) to investigate how labor decisions are influenced by financial incentives (*"Offer"*) as well as by cumulative earnings (ISF) and work hours (HSF) since the beginning of the day. We assume that daily income and time targets, proxied by ISF and HSF, are reset everyday after midnight.

For each shift, we first estimate the choice equation (Equation (6)) in which the outcome variable is a binary decision of whether to work for the focal shift. We then estimate the level equation (Equation (7)) that concerns the work duration for the shift, conditional on the decision to work. We compare three model specifications for the second stage: (i) baseline OLS, (ii) 2SLS without correction for sample selection bias ("two-part model"), and (iii) our main model which is a 2SLS with sample selection correction. Tables 1 and 2 display our estimates for the Midday shift of SUV and sedan drivers, respectively. The first column in each table reports the estimates from the control function probit of the choice equation. The second column reports the estimates from the baseline OLS for the level equation replicating the model implemented in the literature (Camerer et al. 1997, Sheldon 2016). We follow the model specification and IV strategy used in past work.

Covariates include log hourly wage, temperature, rain indicator, day of week, and month dummies and we use the average of other drivers' hourly wages as an instrument. We then present the estimates from the level equation of the two-part model in the third column, and from the level equation of our main model in the fourth column.

Table 1 Estimates of two-stage selection models of SUV drivers' decisions during Midday shifts

	Choice Eq	*Level Eq Baseline*	*Level Eq Two-Part*	*Level Eq Main Model*
Incentives/targets				
Offer/Earnings	0.002*** (0.0006)	−0.083*** (0.019)	0.001 (0.001)	0.001 (0.001)
Income so far	−0.017*** (0.004)	-	−0.009*** (0.002)	−0.008*** (0.002)
Hours so far	2.904*** (0.163)	-	1.690*** (0.068)	1.826*** (0.070)
Hours last week				
Total	0.017*** (0.0003)	-	-	-
Same shift	-	-	0.056*** (0.002)	0.059*** (0.002)
New driver	0.590*** (0.060)	-	-	-
IMR	-	-	-	0.271*** (0.029))
Observations	124,769	45,330	45,329	45,329
R^2	-	0.378	0.552	0.552

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

SUV drivers. For the choice equation, we find that hourly financial offer and cumulative work hours have a significantly positive impact on the decision to work, while cumulative earnings have a significantly negative impact. The first effect indicates that drivers respond positively to an increase in financial incentives as predicted by the standard income effect. The positive effect of HSF suggests that drivers who have worked for a longer period of time during the preceding shift (e.g., AM Peak), controlling for other covariates, are more likely to work for a new shift (e.g., Midday). We refer to this behavior as *inertia*, which we will discuss further as it becomes more prevalent across different analyses. In contrast, the negative effect of ISF reflects a potential income-targeting behavior, that is, drivers are less likely to work if they have earned more income or become closer to their (unobserved) income target. We also find that the number of hours each driver worked in the previous week has a significant positive impact on the decision to work. This could suggest that drivers tend to stick to their work patterns and hold relatively stable work schedules, as observed in Chen et al. (2019). In other words, past work decisions could play an important role in how drivers form and adjust their income and time targets. Lastly, we observe that newer drivers who recently joined the platform are significantly more likely to work.

We next consider the level equation of work duration. Interestingly, under the baseline model, we observe that SUV drivers exhibit a negative income elasticity, similar to full-time taxi drivers investigated in Camerer et al. (1997) and Thakral and Tô (2019), rather than a positive income elasticity observed for ride-hailing drivers (Sheldon 2016). For the other two models in which we incorporate proxies for income and time targets, the estimates for the level equation are relatively consistent regardless of sample selection correction. We observe a directional positive impact of hourly earnings on work duration, providing additional evidence that drivers exhibit positive income elasticity. The impact of ISF is significantly negative, suggesting that income-targeting behavior also negatively affects work duration. On the other hand, the impact of HSF or inertia behavior is significantly positive. We again observe that drivers might stick to their schedules as the work duration for the focal shift is positively affected by the work duration during the same shift in the previous week. In addition, the estimated coefficient of our sample selection correction variable (IMR) is statistically significant, confirming that selection into working is not random. Overall, we observe that the positive effects of hourly earnings and HSF dominate the negative impact of ISF on the work duration.

Table 2 Estimates of two-stage selection models of sedan drivers' decisions during Midday shifts

	Choice Eq	*Level Eq Baseline*	*Level Eq Two-Part*	*Level Eq Main Model*
Incentives/targets				
Offer/Earnings	0.007^{***} (0.0008)	0.080^{***} (0.028)	0.001 (0.001)	0.001 (0.001)
Income so far	-0.031^{***} (0.006)	-	-0.007^{***} (0.002)	-0.007^{***} (0.002)
Hours so far	3.243^{***} (0.192)	-	1.073^{***} (0.058)	1.058^{***} (0.061)
Hours last week				
Total	0.022^{***} (0.0004)	-	-	-
Same shift	-	-	0.079^{***} (0.003)	0.078^{***} (0.003)
New driver	0.660^{***} (0.042)	-	-	-
IMR	-	-	-	-0.029 (0.029)
Observations	113,444	20,307	20,297	20,297
R^2	-	0.389	0.580	0.580
Note:				*p<0.05; **p<0.01; ***p<0.001

Sedan drivers. We perform the same estimation and obtain similar results for sedan drivers: hourly offer or earnings rate and HSF have a positive impact on the decision to work and work duration. Under the baseline approach, we observe that, for sedan drivers, (log) hourly earnings rate positively affects the number of hours worked. The positive income elasticity is in line with findings from ride-hailing drivers in Sheldon (2016). This may suggest that SUV and sedan drivers are fundamentally different types of workers: SUV drivers' behaviors are similar to full-time professional taxi drivers, whereas sedan drivers' behaviors are similar to average drivers on ride-hailing platforms. While descriptive statistics suggest that SUV drivers tend to drive more often and for longer periods relative to sedan drivers, both types of drivers exhibit similar responses to hourly incentive, cumulative earnings, and work hours in the same way under our model. Note that the estimated coefficient for IMR is not statistically significant (at p=0.05) for this shift, suggesting that the evidence of selection of bias is weak. Nevertheless, our insights remain valid as the estimates are consistent regardless of sample selection correction. Furthermore, IMR estimates are statistically significant for all the other shifts (see Appendix A).

Figure 2 **Signs and statistical significance for estimates of two-stage models of drivers' shift-level decisions**

	Choice (Work or not)						**Level** (How long)						
SUV	Mean	IV-F	Offer	ISF	HSF	N	Mean	IV-F	Earn	ISF	HSF	R^2	N
Midday	0.343	372.9	**+**	**-**	**+**	124,769	4.987	180.2	*+*	**-**	**+**	0.552	45,329
PM-Peak	0.277	345.1	**-**	**-**	**+**	131,910	2.421	58.5	**+**	**-**	**+**	0.244	39,592
PM-OPeak	0.182	320.6	**+**	**-**	**+**	130,651	0.731	50.5	**+**	**-**	**+**	0.281	26,699
Late Night	0.117	379.0	**+**	**-**	**+**	125,382	1.996	39.91	**+**	*-*	**+**	0.296	17,137
Sedan	Mean	IV-F	Offer	ISF	HSF	N	Mean	IV-F	Earn	ISF	HSF	R^2	N
Midday	0.137	224.9	**+**	**-**	**+**	113,444	4.186	78.0	*+*	**-**	**+**	0.580	20,297
PM-Peak	0.123	254.7	**-**	**-**	**+**	117,152	2.327	32.6	**+**	**-**	**+**	0.273	19,613
PM-OPeak	0.099	298.8	**+**	**-**	**+**	124,611	0.803	29.9	**+**	**-**	**+**	0.252	17,025
Late Night	0.071	299.5	*+*	**-**	**+**	124,280	2.167	32.9	**+**	**-**	**+**	0.304	15,623

Note: Solid background with bolded **+**: significantly positive, striped with bolded **-**: significantly negative, white with italicized sign: non-significant. All at p = 0.05.

Estimates for other shifts. Figure 2 summarizes the signs and statistical significance of the key estimates (hourly offer/earnings, ISF, and HSF) for each vehicle type and each shift. Each cell in the main three columns is contains the sign of the effect ($+$ or $-$) and the statistical significance at p $=$ 0.05 as follows: solid background with a bolded $+$ indicates a significant positive estimate, striped background with a bolded $-$ indicates a significant negative estimate, and white background with italicized sign corresponds to a non-significant directional effect. In addition, we provide the mean work probability, F-statistics from the first stage of each IV estimation, mean work duration conditional on working, adjusted total R^2, and number of observations alongside the estimates.

We observe that the estimates for drivers of both vehicle types are substantially similar across most shifts. Hourly offers have a consistent positive impact on both choice and level decisions. This result is consistent with the standard income effect that predicts a positive income elasticity and confirms our first hypothesis, that is, financial incentives encourage the decision to work and the work duration. However, we also observe an evidence of behavioral factors of labor supply with regards to cumulative earnings and work hours. The impact of ISF on both stages is significantly negative, suggesting that drivers become less likely to work and work for shorter when they have earned higher cumulative income since the beginning of the work day. This phenomenon reflects an income-targeting behavior among drivers and provides support that labor decisions are negatively influenced by an income targeting behavior, supporting our second hypothesis. Lastly, we observe a fairly surprising effect from HSF on both stages. Specifically, drivers who have previously worked for a longer duration since the beginning of the day are more likely to work in a new shift and for a longer duration. We refer to this phenomenon as *inertia*. Our third hypothesis is hence rejected in the sense that, when controlling for the key covariates, drivers do not exhibit a time-targeting behavior or an aversion to working too many hours. As ISF and HSF have different units, it is not straightforward to compare the magnitude of their effects. Nevertheless, we observe an interesting pattern for the marginal effects on work duration. During earlier shifts in the day, the marginal effect of HSF is larger than that of hourly earnings, but during later shifts, the marginal effect of hourly earnings becomes larger than that of HSF. Fatigue or deteriorated performance discussed in §2.4 seems to be explained by income-targeting behavior rather than by its time counterpart. Putting these together, we conclude that *drivers exhibit positive income elasticity as predicted by the standard income effect but are also influenced by behavioral motives such as an income target and inertia.*

5.2. Across-Day Analysis

Here, we consider the labor decisions drivers make at the beginning each day, whether to work for the day and, if so, for how long. We assume that the week starts on Monday so the income target ISF, the time target HSF, and their progresses are reset at the end of Sunday. In this analysis, ISF and HSF are therefore considered as proxies for *weekly* income and time targets. The covariates in both stages of the estimation are nearly identical to the ones used in §5.1, except that we replace the past work duration on the same *shift* of the previous week by the past work duration on the same *day* of the previous week. Figure 3 displays the estimates from our model for both vehicles types.

Figure 3 Signs and statistical significance for estimates of two-stage models of drivers' day-level decisions

	Choice (Work or not)						**Level** (How long)						
SUV	Mean	IV-F	Offer	ISF	HSF	N	Mean	IV-F	Earn	ISF	HSF	R^2	N
Tuesday	0.409	43.6	*+*	*+*	**+**	28,883	8.696	18.3	*-*	*-*	*+*	0.422	9,482
Wednesday	0.418	55.9	*+*	**+**	**+**	21,965	8.964	26.2	*-*	*-*	*+*	0.422	10,120
Thursday	0.426	73.4	**+**	**+**	**+**	29,233	9.053	34.6	*-*	*-*	**+**	0.412	9,894
Friday	0.412	74.0	**+**	*+*	**+**	20,294	8.915	33.7	*+*	*-*	**+**	0.436	9,283
Saturday	0.203	98.1	**-**	*-*	**+**	15,788	8.435	19.1	*-*	*+*	*-*	0.398	4,372
Sunday	0.162	82.2	**-**	**-**	**+**	13,025	7.927	15.1	**+**	*+*	*-*	0.390	3,240
Sedan	Mean	IV-F	Offer	ISF	HSF	N	Mean	IV-F	Earn	ISF	HSF	R^2	N
Tuesday	0.169	31.1	**+**	*+*	**+**	21,283	7.687	7.3	**-**	*-*	**+**	0.564	4,681
Wednesday	0.182	37.3	**+**	**+**	**+**	23,280	7.680	9.8	*+*	**-**	**+**	0.567	5,278
Thursday	0.179	47.5	**+**	**+**	**+**	19,982	7.724	11.6	*-*	*-*	**+**	0.542	5,081
Friday	0.171	46.7	**+**	**+**	**+**	18,418	7.568	11.2	*-*	*-*	**+**	0.533	4,666
Saturday	0.148	53.3	*+*	*-*	**+**	15,762	8.022	11.7	*-*	*-*	**+**	0.514	3,817
Sunday	0.129	45.5	*-*	**-**	**+**	12,602	7.708	11.4	**+**	**-**	**+**	0.560	3,065

Note: Solid background with bolded text: significantly positive, striped with bolded text: significantly negative, white with italicized text: non-significant. All at p = 0.05.

At a day level, we draw considerably different conclusions from our shift-level analysis. While the positive impact of HSF on a decision to work remains consistent, the impact of hourly offer and ISF appear to vary across different days of the week. Prior to the weekend, both hourly offer and

ISF positively encourage drivers to work. The latter effect might suggest that drivers perceive high cumulative earnings early on in the week as an indicator of high demand and form an optimistic outlook on future market conditions. However, both effects become negative for Saturday and Sunday, resembling less effectiveness of financial incentive and weaker income-targeting behavior. The results for the level equation shed another interesting insight. We do not find significant effects from the three main drivers in most cases, except a consistent inertia observed among sedan drivers. Note that the estimates for the IMR are significant across all cases, suggesting that there is indeed a sample selection bias in the daily work decision. One potential explanation is that, while gig economy workers make strategic decisions of whether to work on a daily basis, they do not seem to decide the work duration for the entire day ahead of time. Instead, they are likely to make such a decision at the shift (or hour) level as observed in our shift-level analysis.

5.3. Discussion

Our results offer a refined explanation of how gig economy workers make labor decisions and, in part, reconcile the debate between neoclassical and behavioral theories of labor supply. Table 3 summarizes our hypotheses and results. We find that, as predicted by the standard income effect, drivers respond positively to financial incentives. While we do not observe the strong negative income elasticity from the literature (such as Camerer et al. 1997), we find empirical evidence of an income-targeting behavior among drivers, suggesting that their labor decisions are influenced by recent earnings or income goals. Several gig economy platforms provide in-app features such as a real-time progress dashboard, making it simple for workers to track their progress and recent earnings and work history. In other words, information surrounding past earnings and work activities have become much more salient relative to traditional settings. By separating cumulative income from financial incentives, we show that the negative impact of income targeting stems from cumulative income rather than the hourly wage. Thakral and Tô (2019) similarly demonstrates the existence of income targeting among taxi drivers and identifies the recently earned cumulative income as a key factor in the decision to quit.

Table 3 Summary of hypotheses and results

	Statement	Shift-level SUV	Shift-level Sedan	Day-level SUV	Day-level Sedan
H1a	Higher wage increases P(work)	✓	✓	✓→ ✗	✓→ ✗
H1b	Higher wage increases work hours	✓	✓	✗	✗
H2a	Higher income so far decreases P(work)	✓	✓	✗→ ✓	✗→ ✓
H2a	Higher income so far shortens work duration	✓	✓	✗	✗
H3a	Longer work hours so far decreases P(work)	✗	✗	✗	✗
H3b	Longer work hours so far shortens work duration	✗	✗	✗	✗

Note: P(work): likelihood of working, ✓: fail to reject, ✗: reject, →: result differs later on in the day or week.

In addition, we establish a new behavioral phenomenon. Workers who have previously worked for a longer duration are more likely to start a new shift and work for longer compared to those who have recently worked less, controlling for all other covariates. We refer to this phenomenon as *inertia* to reflect the tendency of workers with longer recent work hours to continue working and stay active for longer than their counterparts. Our result on inertia is in contrast to findings by Crawford and Meng (2011) and Farber (2015) that taxi drivers exhibit a time-targeting behavior. This difference could be driven by the unique flexibility of gig work. Furthermore, multiple psychological phenomena could potentially explain the existence of inertia, such as reduced fatigue from voluntarily scheduled work (Beckers et al. 2008) and workaholism driven by stochastic and frequent rewards (DeVoe et al. 2010, Corgnet et al. 2020). We also believe that workers' different behaviors towards time versus money could be explained by how people perceive the values of time and money differently. Psychological research has found that mental accounting for time does not work in the same manner as mental accounting for money (Leclerc et al. 1995, Soman 2001). See Appendix D for further discussion. Lastly, we find that gig workers make a decision to work at both shift and day levels, whereas the work duration appears to be decided at a more granular time unit such as a shift or an hour. The latter potentially highlights the unique flexibility of gig jobs that provide workers with full control of their real-time work schedule. Our results remain valid under a number of robustness checks, including the following: allowing for non-linear targeting effects, relaxing our assumption on frequency of target adjustment and definition of shifts, considering instrumental variables for ISF and HSF, performing alternative sample selection correction, and modeling stopping probabilities via mixed-effects survival analysis. With a better understanding of how gig workers make labor decisions, companies can design more effective incentives and personalize them based on individual workers' behaviors.

6. Managerial Implications: Optimal Incentive Allocation

In this section, we illustrate how gig economy firms can use our insights on workers' behavior to enhance their operations. We first investigate the benefit of improved incentive allocation based on two perspectives: (i) increasing service capacity while keeping a fixed budget and (ii) maintaining the same service capacity at a lower cost. We then further highlight the potential pitfalls of ignoring behavioral factors and quantify the resulting capacity loss. Lastly, we conduct a policy analysis to demonstrate how our insights can inform policymakers in developing more effective regulations.

6.1. Targeted Incentives

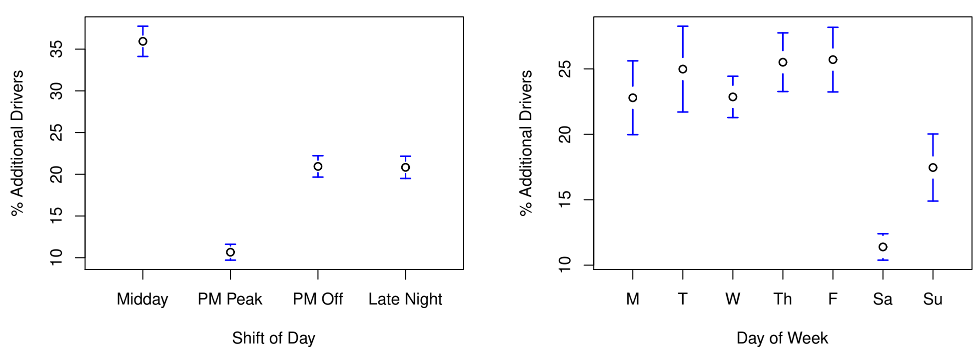
Our main results suggest that workers are influenced by their behavioral motives and that the impact of incentives on the number of active workers may be nonlinear. Targeting specific workers with different incentives can be beneficial. We examine how the platform can improve its operational performance by offering personalized incentives based on workers' attributes. As a benchmark, we compute the platform's budget for promotions based on the actual allocation of incentives. We then re-allocate the promotion budget more efficiently by considering the following two perspectives: (i) increasing the service capacity (i.e., staffing more workers) using the same budget, and (ii) maintaining the same service capacity at a lower cost. Our proposed heuristic ranks the workers by the minimum level of incentives they need to receive in order to start working.

In our context, drivers always receive a guaranteed base pay when they work and sometimes they receive promotions on top of the base rate. We assume that the budget for promotions is separate from the budget for base rates. As not every driver who receives a promotion would choose to work, we compute two types of budget for promotions. First, we compute the total of promotions offered to all drivers for every shift of every day in the data as the *projected budget*. This is the total cost related to promotions incurred by the platform if all drivers chose to work. Second, we compute the actual cost based on the realized number of drivers who showed up to work at any given time as the *realized budget*. We can then compare the service capacity and cost of our heuristic relative to the actual allocation. As our data spans one year from October 2016 to September 2017, we choose the last nine months (January 1–September 30, 2017) as our testing set. For each shift on each day in the testing set, we train our model using all observations from the same shift and day of the week prior to the focal shift. Across 1,012 day-shifts, we observe that 94.59% of drivers were offered a promotion but only 18.4% of them activated the offer and chose to work. Moreover, 94% of the drivers who worked did not receive any promotion. These observations suggest that there is an opportunity to improve the current allocation of financial incentives.

To determine drivers' baseline probability to work, we first compute the average fraction of drivers who worked during a given shift on a given weekday using all past data, denoted by $\bar{D}$. We then compute the inverse c.d.f. evaluated at $\bar{D}$: $\tilde{D} = \Phi^{-1}(\bar{D})$, that is, $\tilde{D}$ represents the argument of $\Phi(\cdot)$ in the right hand-side of Equation (6). In other words, $\tilde{D}$ corresponds to the combination of drivers' attributes that will induce a probability of working equal to $\bar{D}$. For each driver i, we use all the covariates' values with the base pay (e.g., excluding promotions) in our fitted model. This will predict the probability of working when offered only the base rate, $\hat{p}_i^{base}$. If $\hat{p}_i^{base} \geq \tilde{D}$, we label the driver as "driving without promotion." For other drivers, we compute the difference, $\Delta_i = \tilde{D} - \hat{p}_i^{base} > 0$, to determine the level of additional incentive needed for them to work.

Improving service capacity while keeping the same budget. Assuming that the platform has a fixed budget for promotions, we consider a strategy to recruit more workers under the same budget. We first determine the number of drivers who would work regardless of promotions (i.e., their base rates are appealing enough to motivate them to work), and then rank the remaining drivers by increasing values of Δ_i. We compute the *minimum work-inducing promotion level* by dividing Δ_i by the estimated coefficient $\hat{\beta}_{offer}$. We call this value $\tilde{\Delta}_i$. Then, a desired strategy is to allocate the promotion budget first to drivers with the smallest $\tilde{\Delta}_i$ until we exhaust the budget or we can no longer recruit additional drivers. On average, our proposed procedure sends promotions to 6.27% of all available drivers. The 95% interval for the fraction of drivers who should receive a promotion is [0.44%, 19.92%]; these fractions are substantially lower than the current practice of the company. As a result, a much smaller number of drivers would be targeted but each targeted driver would receive a much more attractive promotion. Under the allocation observed in the data, drivers were offered an average promotion of 0.58× relative to their base rate. Under our proposed heuristic, however, targeted drivers receive an average promotion of 2.09×. Ultimately, using the same budget for promotions, our approach can staff 22.1% additional drivers on average with a 95% interval of [2.46%, 50.50%]. Figure 4 reports the percentage increase in the number of drivers for each shift and weekday.

Figure 4 **Number of additional drivers using our allocation strategy**

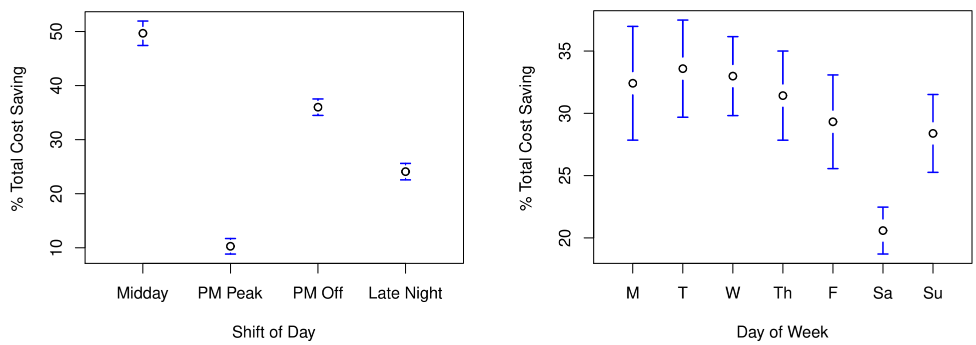


Maintaining service capacity at a lower cost. Companies may have a target level of capacity they hope to meet for several reasons, such as to satisfy a high forecast demand and to maintain low and reliable wait times. Similar to the previous case, we rank all drivers by increasing values of the minimum work-inducing promotion level (i.e., $\tilde{\Delta}_i$). We subtract the number of drivers who are predicted to work without any promotion from the desired service capacity. Instead of having a budget constraint, we now allocate promotions to drivers who require the smallest incentive $\tilde{\Delta}_i$ until we reach the desired service capacity. On average, the allocation under our heuristic costs 30.10% less relative to current practice with a 95% interval of [0.75%, 63.54%]. Figure 5 shows the percentage of cost savings for each shift and weekday.

6.2. Impact of Behavioral Explanations of Labor Decisions

In this section, we quantify the impact of capturing the main behavioral factors obtained in our estimation results. To this end, we investigate how many workers the platform would fail to attract if it did not incorporate income targeting and inertia into incentive design. We compare the following three scenarios to our model:

Figure 5 **Simulated cost savings while maintaining the same service capacity**



(a) *ISF Only*: The firm assumes that work decisions are influenced by ISF but not HSF.

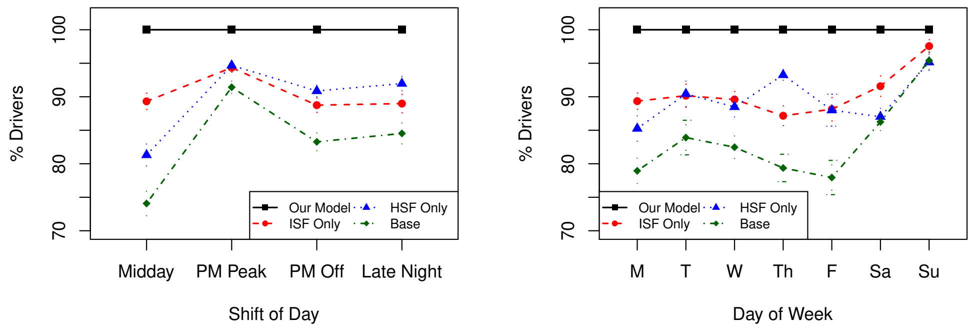
(b) *HSF Only*: The firm assumes that work decisions are influenced by HSF but not ISF.

(c) *Base*: The firm ignores both income-targeting and inertia behaviors.

Our analysis is at the day-shift level and reports out-of-sample predictions. The testing set consists of each day-shift between January 1, 2017 and September 30, 2017. For each day-shift in the testing set, we train four separate choice equations—one for each model (a)-(c) above and one for our model—using all historical observations of the same day-shift from October 2016 to the week prior to the focal date. Each of the four choice equations represents the predicted outcome depending on the platform's assumption on workers' behavior. We first compute the fraction of drivers' work decisions that each model predicts correctly out-of-sample relative to the actual realization in the data. On average, our model outperforms the other three models in prediction accuracy both at the shift and day levels. Specifically, when the company ignores behavioral drivers of labor decisions, it loses 8.6% in prediction accuracy on average. Following the same procedure as in §6.1, we compute the incentive allocation under each model. More precisely, we first assume that each model is the true state of the world and solve for the optimal incentive allocation given the promotion budget observed in the data. Once the allocation is completed, we estimate the expected number of drivers who would be working, assuming that the true state of the world is actually governed by our model. Note that by construction, our model will always outperform the other models in terms of the expected capacity. Our main goal here is to quantify the magnitude of capacity loss when the company make different assumptions about workers' behavior.

Figure 6 shows that ignoring behavioral factors can lead to a significant loss in the number of active drivers. Specifically, the Base model leads to an average loss of 16.70% in the expected number of active drivers relative to our model, with a standard deviation of 13.06%. The ISF Only (HSF Only) model leads to an average reduction of 9.63% (10.32%) in the expected number of active drivers with a standard deviation of 9.10% (10.20%).

Figure 6 **Impact of ignoring behavioral factors on the expected number of active drivers**



In summary, these results suggest that it is important for gig platforms to account for income targeting and inertia. Ignoring these behavioral motives can decrease prediction accuracy, and more importantly, induce misleading incentive decisions that may result in suboptimal capacity levels.

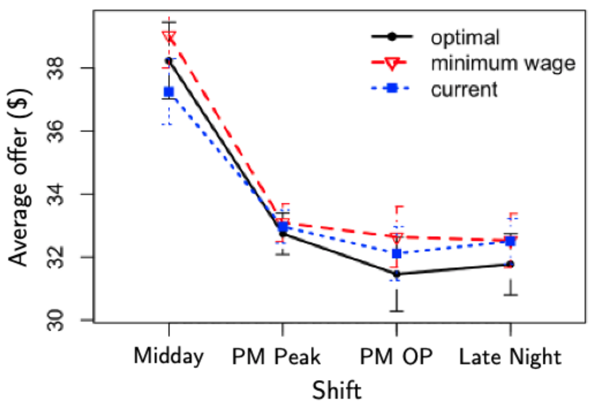
6.3. Policy Analysis: NYC's Driver Income Rules

Finally, we take a view of a policymaker and employ our insights to evaluate the impact of regulations on the welfare of gig workers. In December 2018, TLC passed *Driver Income Rules* to protect driver earnings, requiring ride-hailing platforms to compensate drivers a minimum amount for each trip at the rate equivalent to \$27.86 per hour. Since there were no such rules during the timeframe of our data, we can perform a counterfactual analysis to quantify the impact of new regulations on the workers' welfare, particularly their earnings.

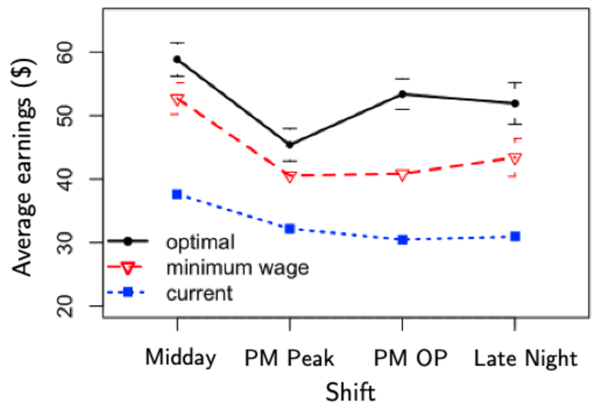
We compare three different policies. First, our *optimal* policy is the targeted incentive allocation policy introduced in §6.1, which optimizes incentives based on drivers' predicted probability to work. Second, a *minimum wage* policy adds a constraint to the optimal policy such that every driver must be guaranteed a minimum hourly offer of \$27.86. Finally, we use the observed incentives in the data as a benchmark or *current* practice. Outcomes of interest are the average hourly offer across all drivers and the average hourly earnings across drivers who are predicted to work. The counterfactuals are performed for data between January and September 2017 in the same fashion as in §6.1.

Figure 7a shows that the minimum wage policy slightly increases the average hourly offer among drivers compared to the optimal policy and current practice, but the differences are not statistically significant. However, these policies lead to significantly different average hourly earnings among drivers predicted to work. Figure 7b suggests that, compared to the current practice, the minimum wage policy significantly improves the average hourly earnings. However, drivers could have earned 10 to 23% more per hour if the incentives were optimally allocated by following the optimal policy without the minimum wage constraint.

Figure 7 Average hourly offer and earnings across three policies.



(a) Average hourly offer across all drivers



(b) Average hourly earnings across drivers who worked.

The minimum wage policy appears to be beneficial to the workers compared to the platform's current practice. However, as firms are becoming more data-driven and potentially adopting more sophisticated incentive policies (such as our proposed optimal policy), the current minimum wage rule may no longer improve the welfare of the workers. In this case, if the focal platform implements the optimal policy, the regulation decreases workers' pay on average. This also highlights the importance of understanding how gig workers make decisions. TLC does have detailed information regarding trips operated by ride-hailing drivers but may not have access to how the platforms allocate incentives or how drivers decide their flexible schedules. Without such knowledge, policymakers are prone to regulations that could be suboptimal.

7. Concluding Remarks

The recent rise of the gig economy has changed the way people think about employment. Unlike traditional employees who work under a fixed schedule, gig economy workers are free to choose their own schedule and platform to provide service. Such flexibility poses a great challenge to gig platforms in terms of planning and committing to a service capacity. It also poses a challenge to policymakers who are concerned about protecting workers. In this paper, we propose a framework to investigate how gig economy workers make labor decisions. Using data from a ride-hailing platform, we develop an econometric model that accounts for sample selection and endogeneity and controls for the competition within the ride-hailing industry. We find that financial incentives have a positive effect on the decision to work and on the work duration, confirming the positive income elasticity from the standard income effect. We also observe the influence of behavioral factors through the accumulated earnings and number of hours previously worked. The dominating effect, inertia, suggests that the longer workers have been working so far, the more likely they will continue working and the longer duration they will work for. Our results also reflect a unique feature of gig work. While workers decide whether to work on both shift and day levels, they decide on work duration on a shift basis. Finally, our numerical experiments demonstrate that gig platforms can benefit from incorporating our insights into their incentive optimization.

One of the important phenomena that emerge from this paper is the existence of inertia among drivers. While we cannot conclude that all gig economy workers exhibit such a behavior, we believe that it has important implications that go beyond this study. Indeed, we believe the findings are generalizable to other flexible workforces. Drivers in our data are not exclusive to the focal platform and are often working for other gig companies. Policies used by the focal platform are also quite common in the industry, from delivery to tutoring services. Therefore, there is a lesson to be learned about the fundamental impact of such policies. Amidst intensifying competition among providers of similar on-demand services, companies are making every effort to win over a mutual pool of workers. This paper empirically identifies several key behavioral factors that affect gig economy workers' decisions. These findings can be used to sharpen platforms' understanding on how gig economy workers make labor decisions, and ultimately improve platforms' operational decisions (e.g., sending the right offer to the right worker at the right time).

This paper opens several avenues for future research. It could be interesting to validate our findings by running a controlled field experiment. Given that online platforms routinely run experiments to confirm insights, testing the income targeting and inertia effects could be of interest. A second direction is to further investigate how workers construct their reference points or targets in both financial and time dimensions, and how these targets are updated over time. This will allow companies to gain insights about the (dis)utility of working as well as understanding how workers switch between service providers. Finally, our incentive allocation is based on simple ranking arguments. Developing a more comprehensive optimization framework to optimize incentives for each driver in each shift under further operational constraints is also an interesting extension. The main goals of this research stream would be to refine our understanding of gig economy workers and develop data-driven methods that can be used by gig platforms to efficiently motivate and strengthen their relationships with their flexible workforce.

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Appendix A: Additional Details of the Main Results

Figures A1 and A2 provide additional details of the main results from our two-stage models of drivers' decisions on a shift level and a day level, respectively. For each of the key variables, we provide an estimated coefficient and a standard error in parenthesis. Within each model, we also report an estimated coefficient and a standard error for IMR and two R-squared's, total R-squared (top) and within R-squared (bottom, italicized). We acknowledge that a few of the IMR estimates are not statistically significant, suggesting that the selection bias is weak in some cases. However, our insights regarding the impact of financial incentives, cumulative income, and cumulative work hours on the decisions of both stages are consistent across different model specifications and selection approaches (e.g., two-part model and Dahl's correction).

Figure A1 Estimates of two-stage models of drivers' shift-level decisions

	Choice (Work or not)				**Level** (How long)					
SUV	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Midday	**0.0024** **(0.0006)**	**-0.0173** **(0.0036)**	**2.9044** **(0.1632)**	124,769	0.001 (0.001)	**-0.008** **(0.002)**	**1.826** **(0.070)**	**0.271** **(0.029)**	0.552 *0.239*	45,329
PM-Peak	**-0.0177** **(0.0013)**	**-0.0022** **(0.0002)**	**0.5020** **(0.0082)**	131,910	**0.023** **(0.005)**	**-0.0004** **(0.0001)**	**0.316** **(0.009)**	**0.627** **(0.043)**	0.244 *0.092*	39,592
PM-OPeak	**0.0018** **(0.0008)**	**-0.0024** **(0.0001)**	**0.3436** **(0.0048)**	130,651	**0.003** **(0.001)**	**-0.0001** **(0.00003)**	**0.020** **(0.002)**	0.009 (0.011)	0.281 *0.029*	26,699
Late Night	**0.0035** **(0.0010)**	**-0.0024** **(0.0001)**	**0.2817** **(0.0047)**	125,382	**0.025** **(0.002)**	-0.0002 (0.0001)	**0.022** **(0.011)**	-0.088 (0.054)	0.296 *0.027*	17,137
Sedan	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Midday	**0.0068** **(0.0008)**	**-0.0309** **(0.0056)**	**3.2429** **(0.1916)**	113,444	0.001 (0.001)	**-0.007** **(0.002)**	**1.058** **(0.061)**	-0.029 (0.029)	0.580 *0.206*	20,297
PM-Peak	**-0.0109** **(0.0016)**	**-0.0013** **(0.0004)**	**0.4787** **(0.0133)**	117,152	**0.020** **(0.004)**	**-0.001** **(0.0002)**	**0.116** **(0.009)**	**-0.120** **(0.034)**	0.273 *0.014*	19,613
PM-OPeak	**0.0031** **(0.0010)**	**-0.0028** **(0.0003)**	**0.4133** **(0.0090)**	124,611	**0.003** **(0.0005)**	**-0.0002** **(0.00004)**	**0.005** **(0.002)**	**-0.098** **(0.007)**	0.252 *0.029*	17,025
Late Night	0.0018 (0.0014)	**-0.0021** **(0.0002)**	**0.3356** **(0.0082)**	124,280	**0.036** **(0.004)**	**-0.001** **(0.0002)**	**0.063** **(0.011)**	**-0.378** **(0.048)**	0.304 *0.026*	15,623

Note: Green background with bolded **"+"**: significantly positive, yellow with bolded **"-"**: significantly negative, white with italicized sign: non-significant. All at p = 0.05.

Figures A3 and A4 provide the effect sizes for an average driver at shift and day levels, respectively, when one of the following conditions happens: (i) a \$10 increase in hourly offer or earning rate, (ii) a \$10 increase in ISF, and (iii) an additional hour to HSF.

Appendix B: Alternative Empirical Approaches

B.1. Sample Selection Bias Correction

B.1.1. Dahl's correction. Following Dahl (2002) and Bray et al. (2019), we use the selection probability as a sufficient statistic for the selection bias. Since, in our context, the choice for each driver is only binary: to work or not, we do not suffer from a curse of dimensionality. Revisiting our level equation (Equation (7)),

$$f(Hour_{i,t}) = \beta_{0,i} + \beta_{\tilde{w}}\tilde{w}_{i,t} + \beta_{ISF}ISF_{i,t} + \beta_{HSF}HSF_{i,t} + \beta\mathbf{Z_{i,t}} + \theta\lambda_{i,t} + u_{i,t},$$

we can substitute IMR (λ) with all basis functions of a B-spline with using the quantiles of work probabilities for all drivers, $\mathbf{P_{work}} = [P(Drive_{i,t} = 1|\mathbf{X_{i,t}}), \forall i]$ as interior knots. Let $\mathfrak{B}(\mathbf{P_{work}}, j)$ be the j^{th} basis

Figure A2 **Estimates of two-stage models of drivers' day-level decisions**

	Choice (Work or not)				**Level** (How long)					
SUV	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Tuesday	0.0039 (0.0021)	0.0006 (0.0003)	**0.0581 (0.0137)**	28,883	-0.003 (0.010)	-0.001 (0.001)	0.027 (0.029)	**-1.711 (0.184)**	0.422 *0.037*	9,482
Wednesday	0.0036 (0.0020)	**0.0005 (0.0002)**	**0.0461 (0.0087)**	21,965	-0.001 (0.008)	-0.0003 (0.0005)	0.028 (0.021)	**-1.274 (0.192)**	0.422 *0.040*	10,120
Thursday	**0.0087 (0.0019)**	**0.0005 (0.0001)**	**0.0358 (0.0061)**	29,233	-0.006 (0.008)	-0.0004 (0.0003)	**0.042 (0.014)**	**-0.973 (0.217)**	0.412 *0.046*	9,894
Friday	**0.0069 (0.0019)**	0.00001 (0.0001)	**0.0506 (0.0046)**	20,294	0.013 (0.008)	-0.0004 (0.0002)	**0.055 (0.012)**	0.007 (0.229)	0.436 *0.031*	9,283
Saturday	**-0.0246 (0.0036)**	-0.0002 (0.0001)	**0.0292 (0.0038)**	15,788	-0.002 (0.030)	0.0001 (0.0003)	-0.013 (0.017)	**-2.149 (0.640)**	0.398 *0.045*	4,372
Sunday	**-0.0216 (0.0034)**	**-0.0006 (0.0001)**	**0.0504 (0.0040)**	13,025	**0.049 (0.024)**	0.00005 (0.0004)	-0.032 (0.021)	**-3.102 (0.580)**	0.390 *0.040*	3,240
Sedan	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Tuesday	**0.0216 (0.0028)**	0.0008 (0.0007)	**0.0766 (0.0221)**	21,283	**-0.040 (0.015)**	-0.002 (0.002)	**0.070 (0.035)**	**-0.940 (0.141)**	0.564 *0.097*	4,681
Wednesday	**0.0128 (0.0027)**	**0.0016 (0.0004)**	**0.0435 (0.0142)**	23,280	0.015 (0.012)	**-0.002 (0.001)**	**0.122 (0.023)**	**-0.657 (0.150)**	0.567 *0.114*	5,278
Thursday	**0.0115 (0.0026)**	**0.0010 (0.0003)**	**0.0351 (0.0095)**	19,982	-0.002 (0.011)	-0.00004 (0.0005)	**0.052 (0.016)**	-0.254 (0.164)	0.542 *0.100*	5,081
Friday	**0.0173 (0.0024)**	**0.0004 (0.0002)**	**0.0375 (0.0068)**	18,418	-0.009 (0.011)	-0.00002 (0.0004)	**0.026 (0.013)**	-0.321 (0.209)	0.533 *0.067*	4,666
Saturday	0.0035 (0.0049)	-0.0003 (0.0002)	**0.0502 (0.0062)**	15,762	-0.006 (0.028)	-0.0002 (0.0004)	**0.038 (0.014)**	-0.066 (0.311)	0.514 *0.067*	3,817
Sunday	-0.0081 (0.0046)	**-0.0007 (0.0002)**	**0.0626 (0.0063)**	12,602	**0.058 (0.022)**	**-0.001 (0.0004)**	**0.062 (0.015)**	-0.317 (0.342)	0.560 *0.101*	3,065

Note: Green background with bolded **"+"**: significantly positive, yellow with bolded **"-"**: significantly negative, white with italicized sign: non-significant. All at p = 0.05.

Figure A3 **Effect sizes of changes in hourly financial offer/earnings, ISF, and HSF on drivers' shift-level decisions**

	% Change in P(Work)					Change in Duration (mins)				
SUV	Mean	+\$10 Offer	+\$10 ISF	+1h HSF	N	Mean	+\$10 Earn	+\$10 ISF	+1h HSF	N
Midday	0.343	**0.82**	**-5.73**	**57.21**	124,769	4.987	*0.51*	**-4.87**	**109.53**	45,329
PM-Peak	0.277	**-4.39**	**-0.57**	**15.27**	131,910	2.421	**13.64**	**-0.24**	**18.96**	39,592
PM-OPeak	0.182	**0.27**	**-0.36**	**6.43**	130,651	0.731	**1.72**	**-0.08**	**1.18**	26,699
Late Night	0.117	**0.34**	**-0.22**	**3.32**	125,382	1.996	**14.87**	-0.11	**1.35**	17,137
Sedan	Mean	+\$10 Offer	+\$10 ISF	+1h HSF	N	Mean	+\$10 Earn	+\$10 ISF	+1h HSF	N
Midday	0.137	**1.28**	**-4.70**	**84.74**	113,444	4.186	*0.75*	**-4.21**	**63.46**	20,297
PM-Peak	0.123	**-1.45**	**-0.18**	**9.08**	117,152	2.327	**11.99**	**-0.50**	**6.95**	19,613
PM-OPeak	0.099	**0.31**	**-0.28**	**5.59**	124,611	0.803	**1.62**	**-0.11**	**0.33**	17,025
Late Night	0.071	*0.18*	**-0.20**	**4.12**	124,280	2.167	**21.65**	**-0.83**	**3.81**	15,623

Note: Solid background with bolded text: significantly positive, striped with bolded text: significantly negative, white with italicized text: non-significant. All at p = 0.05.

function of a degree n B-spline with the quantiles of $\mathbf{P_{work}}$ as m interior knots. Also, define $\eta_{i,t} = u_{i,t} - \sum_{j=0}^{m+n} \gamma_j \mathfrak{B}(\mathbf{P_{work}}, j)$ to maintain the orthogonality of the error term and the expected hours worked. Thus,

Figure A4 **Effect sizes of changes in hourly financial offer/earnings, ISF, and HSF on drivers' day-level decisions**

	% Change in P(Work)					Change in Minutes Worked				
SUV	Mean	+$10 Offer	+$10 ISF	+1h HSF	N	Mean	+$10 Earn	+$10 ISF	+1h HSF	N
Tuesday	0.409	1.53	0.24	**2.26**	28,883	8.696	-2.03	-0.45	1.65	9,482
Wednesday	0.418	1.39	**0.19**	**1.81**	21,965	8.964	-0.46	-0.18	1.70	10,120
Thursday	0.426	**3.36**	**0.20**	**1.38**	29,233	9.053	-3.71	-0.26	**2.54**	9,894
Friday	0.412	**2.70**	0.01	**1.96**	20,294	8.915	7.51	-0.27	**3.31**	9,283
Saturday	0.203	**-6.23**	-0.05	**0.83**	15,788	8.435	-1.42	0.03	-0.76	4,372
Sunday	0.162	**-5.04**	**-0.16**	**1.33**	13,025	7.927	**29.32**	0.03	-1.90	3,240
Sedan	Mean	+$10 Offer	+$10 ISF	+1h HSF	N	Mean	+$10 Earn	+$10 ISF	+1h HSF	N
Tuesday	0.169	**6.19**	0.21	**2.08**	21,283	7.687	**-23.80**	-0.92	**4.23**	4,681
Wednesday	0.182	**3.71**	**0.44**	**1.22**	23,280	7.680	8.81	**-1.38**	**7.31**	5,278
Thursday	0.179	**3.19**	**0.26**	**0.95**	19,982	7.724	-1.26	-0.02	**3.10**	5,081
Friday	0.171	**4.85**	**0.11**	**1.00**	18,418	7.568	-5.56	-0.01	**1.55**	4,666
Saturday	0.148	0.89	-0.08	**1.29**	15,762	8.022	-3.57	-0.12	**2.27**	3,817
Sunday	0.129	-1.98	**-0.18**	**1.63**	12,602	7.708	**34.52**	**-0.63**	**3.72**	3,065

Note: Green background with bolded **"+"**: significantly positive, yellow with bolded **"-"**: significantly negative, white with italicized sign: non-significant. All at p = 0.05.

our level equation under this approach becomes:

$$f(Hour_{i,t}) = \beta_{0,i} + \beta_{\tilde{w}}\tilde{w}_{i,t} + \beta_{ISF}ISF_{i,t} + \beta_{HSF}HSF_{i,t} + \beta\mathbf{Z_{i,t}} + \sum_{j=0}^{m+n}\gamma_j\mathfrak{B}(\mathbf{P_{work}}, j) + \eta_{i,t}. \tag{B1}$$

In Figure B5, we present the estimates for the level equation when choosing $m = n = 3$. Our results remain consistent under both approaches for sample selection correction. Note that, for all but sedan drivers' decisions on Friday and Saturday, the selection variables are significant at p = 0.05, confirming that there exists a selection bias in the decision to work.

B.2. Instrumental Variables

B.2.1. Co-skippers IV. This IV follows a similar idea to our main IV, but instead of matching drivers based on their past work decisions at a specific time in the past, we now match drivers based on the level of past inactivity. For every day in our data, we categorize drivers into four groups based on each quartile of the number of consecutive days they have been inactive. We call the drivers of a different vehicle type who belong to the same group *co-skippers*. This IV satisfies the *relevance condition:* Since both the focal driver and their co-skippers have been inactive for approximately the same time, their incentives should be highly correlated. From the first stage of our IV estimation, the estimate for the instrument is consistently signifiant and F-statistics across all models except one are larger than the conventional threshold of 10. This IV also satisfies the *exclusion restriction:* Current incentives for co-skippers should not directly influence the focal driver's work decision because (i) they drive different vehicle types and (ii) the focal driver does not have access to co-skippers' incentives information.

Figure B5 Estimates for the level equation using Dahl's correction

	SUV Drivers			Sedan Drivers		
Shift	Earning	ISF	HSF	Earning	ISF	HSF
Midday	+	+	+	+	+	+
PM-Peak	+	-	+	+	-	+
PM-OPeak	+	-	+	+	-	+
Late Night	+	-	+	+	-	+
Day	Earning	ISF	HSF	Earning	ISF	HSF
Tuesday	-	-	+	-	-	+
Wednesday	+	-	+	+	-	+
Thursday	-	-	+	+	+	+
Friday	-	-	+	-	+	+
Saturday	-	+	-	-	+	-
Sunday	-	+	-	+	-	+

Note: Green background with bolded "+": significantly positive, yellow with bolded "-": significantly negative, white with italicized sign: non-significant. All at p = 0.05.

The estimates from shift- and day-level analyses are consistent with our main results. Figure B6 presents the signs and statistical significance (at p=0.05) of the estimates across shifts and days. However, these models are outperformed by our main models in both in-sample and out-of-sample prediction accuracy.

Figure B6 Estimates across shifts and days using the co-skippers IV

	Choice (Work or not)				Level (How long)			
SUV	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Midday	433.1	+	+	+	266.8	+	+	+
PM-Peak	289.5	-	-	+	58.7	+	-	+
PM-OPeak	260.2	+	-	+	45.1	+	-	+
Late Night	329.9	+	-	+	36.4	+	-	+
Sedan	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Midday	229.2	+	+	+	104.4	+	+	+
PM-Peak	231.3	+	-	+	31.8	+	-	+
PM-OPeak	255.9	+	-	+	24.3	+	-	+
Late Night	270.0	+	-	+	30.9	+	-	+

	Choice (Work or not)				Level (How long)			
SUV	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Tuesday	37.9	-	+	+	21.1	-	-	+
Wednesday	41.3	+	+	+	25.5	-	-	+
Thursday	67.9	+	-	+	43.9	-	+	+
Friday	67.5	+	+	+	41.9	-	-	+
Saturday	89.1	+	+	+	19.4	-	+	-
Sunday	82.1	-	-	+	16.0	+	+	-
Sedan	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Tuesday	25.3	+	+	+	8.8	-	-	+
Wednesday	24.9	+	+	+	10.6	+	-	+
Thursday	43.9	+	+	+	15.8	+	-	+
Friday	39.9	+	+	+	13.6	-	+	-
Saturday	58.3	+	+	+	12.8	-	+	-
Sunday	48.7	-	-	+	12.5	+	-	+

Note: Green background with bolded "+": significantly positive, yellow with bolded "-": significantly negative, white with italicized sign: non-significant. All at p = 0.05.

B.2.2. Hausman-type IV. Inspired by previous studies such as Sheldon (2016), we use the average hourly offer rate received by all other registered drivers during the same shift on the same day as an instrument for the offer rate. Similarly, we use the average hourly earnings rate earned by all other active drivers during the same shift on the same day as an instrument for the hourly earnings rate. These instruments can be thought of as a mutual offer or earning rate for eligible drivers in New York City at a particular time. In addition, the incentives offered to other drivers should not directly influence the focal driver's decision to work. Controlling for weather and market conditions using the TLC data, we rule out potential confounders that affect both the variation in incentives and the labor decisions. Unlike other ride-hailing platforms, drivers on our platform do not compete with other drivers for promotions as both the base and promotional rates are decided and announced ahead of time. Moreover, promotions are not offered as a way to relocate drivers to high-demand areas (see §3.3 for more details). Thus, it suggests that this IV satisfies the exclusion restriction. The results we obtained using this IV are qualitatively similar as illustrated in Figure B7. While this type of IV appears to be valid for the choice equation, low F-statistics suggest that it is a relatively weaker IV relative to both the co-workers and co-skippers IVs.

Figure B7 **Estimates across shifts and days using Hausman-type IV**

	Choice (Work or not)				Level (How long)			
SUV	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Midday	365.4	+	+	+	183.7	+	+	+
PM-Peak	318.8	-	-	+	56.9	+	-	+
PM-OPeak	301.7	+	-	+	49.1	+	-	+
Late Night	371.7	+	-	+	38.1	+	-	+
Sedan	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Midday	223.2	+	+	+	81.1	+	+	+
PM-Peak	255.6	-	-	+	32.9	+	-	+
PM-OPeak	274.9	+	-	+	27.3	+	-	+
Late Night	278.6	+	-	+	29.8	+	-	+

	Choice (Work or not)				Level (How long)			
SUV	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Tuesday	41.4	+	+	+	18.1	-	-	+
Wednesday	52.2	+	+	+	24.5	+	-	+
Thursday	61.6	+	-	+	33.2	-	+	+
Friday	62.3	+	+	+	29.8	-	-	+
Saturday	83.1	+	+	+	15.2	-	+	-
Sunday	70.9	+	-	+	11.5	+	+	-
Sedan	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Tuesday	30.3	+	+	+	8.0	-	-	+
Wednesday	35.3	+	+	+	10.3	+	-	+
Thursday	42.6	+	+	+	12.9	+	+	+
Friday	39.5	+	+	+	10.6	-	+	-
Saturday	44.4	+	-	+	9.8	-	+	-
Sunday	40.7	+	-	+	7.9	+	-	+

Note: Green with "+": significantly positive, yellow with "-": significantly negative, white: non-significant at p = 0.05.

B.3. Addressing the Multicollinearity Concern

Correlations between ISF and HSF in our data range from 0.446 to 0.929, depending on the time of the day and the vehicle type. While these correlations appear to be on a high side, we gain sufficient statistical power by leveraging our large sample size. Based on Mason and Perreault Jr (1991), our levels of collinearity are between Levels II and III. Given that our R-squared is between 0.25 and 0.5, the minimum sample size of 300 is required. In our case, this requirement is readily satisfied since we have over 100,000 observations for each vehicle type and shift.

Nevertheless, we consider alternative model specifications that still allow us to investigate both the impact of ISF and HSF on the labor decisions. For conciseness, we present one major approach below. The insights remain valid in all specifications.

B.3.1. Localized hazard regressions. Motivated by Thakral and Tô (2019), we estimate additional models when controlling for drivers who either had the same amount of accumulated earnings or the same amount of time worked so far. Such a specification allows for a flexible, driver-specific hazard of stopping and a time-dependent relationship between each of the covariates and the stopping probability. After driving t trips and accumulating y_{int} from working a total of h_{int} hours, driver i decides to end shift n when the cost of additional effort exceeds the expected continuation value. y_{int} and h_{int} represent income so far (ISF) and hours so far (HSF) in our setting. Let d_{int} be the decision to stop working after trip t in shift n. Thakral and Tô (2019) models the probability that driver i ends shift n at trip t by

$$\mathbb{P}(d_{int}=1)=f(h_{int})+\beta(h_{int})y_{int}+X_{int}\gamma(h_{int})+\mu_i(h_{int})+\epsilon_{int},$$

where $f(\cdot)$ represents the baseline hazard and μ absorbs differences in drivers' baseline stopping tendencies. HSF affects the stopping probability through the baseline hazard and the impact of ISF, covariates, and drivers' fixed effects. $\beta(h)$ reflects the effect of an additional dollar of ISF on the probability of ending a shift for a driver after h hours of work ($HSF=h$). Thakral and Tô (2019) employs local linear regressions to estimate the baseline hazard and the time-varying coefficients by solving a separate weighted least squares problem:

$$\min_{\alpha,\beta,\gamma,\mu_i}\sum_{i,n,t} w(h_{int}-h)(d_{int}-(\alpha h_{int}+\beta y_{int}+X_{int}\gamma+\mu_i))^2$$

with weights given by $w(\cdot)$. With uniform weights, this procedure becomes fitting a linear model to a localized subset of data. We consider time windows of different interval: 10, 15, 20, 30, and 60 minutes.

We consider two models:

(i) *HSF impacts how ISF affects the stopping probability.* This is similar to the model formulated in Thakral and Tô (2019). We model the probability that driver i stops working at time t of day n after earning ISF_{int} and spending HSF_{int} hours working for the day as:

$$\mathbb{P}(d_{int}=1)=f(HSF_{int})+\beta^w(HSF_{int})w_{int}+\beta^ISF(HSF_{int})ISF_{int}+X_{int}\gamma(HSF_{int})+\mu_i(HSF_{int})+\epsilon_{int},$$

where w_{int} is the hourly financial incentive offered at time t of day n. We include the hourly incentive to match our main models and reflect the possibility that drivers are less likely to quit if the current offer is appealing. The local regressions are done by controlling for drivers who were still active at the population median of HSF.

(ii) *ISF impacts how HSF affects the stopping probability.* This model is to validate our findings that drivers exhibit inertia, affecting their work decisions. Using the notation from our setting, we model the probability that driver i stops working at time t of day n after earning ISF_{int} and spending HSF_{int} hours working for the day as:

$$\mathbb{P}(d_{int}=1)=f(ISF_{int})+\beta^w(ISF_{int})w_{int}+\beta^HSF(ISF_{int})HSF_{int}+X_{int}\gamma(ISF_{int})+\mu_i(ISF_{int})+\epsilon_{int},$$

The local regressions are done by controlling for drivers who were still active when earning cumulative income of the population median of ISF.

Results for Model (i): Impact of ISF. The median number of hours that drivers worked on non-holiday weekdays is 6.72 hours for SUV drivers and 6.58 hours for sedan drivers. Table B1 presents estimates for the local probit models of the decision to quit within 10, 15, 30, or 60 minutes after reaching the population median HSF. The results confirm that financial incentives decrease the quitting probability while cumulative earnings tend to increase the quitting probability. Under the assumption that cumulative hours worked (HSF) only affect the quitting probability through the impact offers and ISF, we confirm that income targeting exists while drivers appear to have positive income elasticity.

Table B1 Estimates of local probit models of quitting decision controlling for cumulative work hours (HSF)

Quit within	SUV		Sedan	
	Offer	ISF	Offer	ISF
10 mins	−0.0174	0.0004	−0.0340	0.0025
15 mins	-0.0199^{*}	0.0014	-0.0365^{*}	0.0040^{*}
30 mins	-0.0204^{**}	0.0023^{*}	-0.0321^{**}	0.0039^{**}
1 hour	−0.0047	0.0011	−0.0165	0.0016
Note:	*p<0.05; **p<0.01; ***p<0.001			

Results for Model (ii): Impact of HSF. We perform a similar analysis where we assume that the impact of ISF is only through the varying impact of HSF. The median cumulative earnings drivers made on non-holiday weekdays are \$219.73 for SUV drivers and \$199.01 for sedan drivers. Table B2 shows that significant inertia is observed among SUV and sedan drivers when the time window of quitting decision is between 10 and 30 minutes. We also find that the hourly financial offer consistently decreases the stopping probability except for large SUV drivers where the effect is opposite.

Table B2 Estimates of local probit models of quitting decision controlling for cumulative earnings (ISF)

Quit within	SUV		Sedan	
	Offer	HSF	Offer	HSF
10 mins	−0.18	−0.0652	−0.0047	0.0349
15 mins	-0.0252^{***}	-0.1003^{***}	−0.0091	0.0019
30 mins	-0.0186^{***}	-0.0718^{***}	-0.021^{***}	-0.1103^{***}
1 hour	-0.0202^{**}	−0.0235	-0.0182^{***}	0.0228
Note:	*p<0.05; **p<0.01; ***p<0.001			

B.4. Alternative Construction of ISF and HSF

We first argue that our assumption that the progress towards a daily income or time goal is reset at midnight is reasonable. 91.07% of drivers' working days observed in our data do not overlap with midnight (e.g., they did not work overnight). Furthermore, 99.93% started working between 5am and 11pm. Therefore, we believe that drivers consider a new calendar day as a new progress. However, it is plausible that drivers do not reset their weekly goals every Monday. As a robustness study, we relax the assumptions that the weekly targets are reset every Monday. Instead, drivers might reset the across-day goals only when they start working after being inactive for some time. In this direction, we analyzed the duration of inactivity between any consecutive working days. Among 7,800 drivers who worked at least two days in the dataset, the average number of inactive days between two working days is 2.21 days. 15% drivers worked everyday on average and 53.30% did not take more than 2 days break. We re-estimated our models by allowing the targets to be reset every time the drivers did not work for at least two days.

Table B3 illustrates that, allowing the weekly targets to be reset after taking time off from work, our original insights remain qualitatively consistent. In the first stage, positive income elasticity is significant throughout the week. Income targeting and inertia are significant on Mondays and Tuesdays, but their respective directions remain generally consistent for the rest of the week. In the second stage, hourly earnings do not have significant effect. Income targeting appears to only be significant on Tuesdays, Saturdays, and

Sundays, but the negative direction is consistent. We observe that inertia are generally significant and apparent from Fridays to Tuesdays.

Table B3 Estimates for the day-level two-stage estimation for sedan drivers when weekly targets were reset after at least 2 days of inactivity.

	Stage 1: Work or not?			Stage 2: How long, conditional on working?			
Sedan	Offer	ISF	HSF	Earnings	ISF	HSF	IMR
Monday	0.026401***	-0.000376***	0.008667***	-0.027	-0.0002	0.008+	***
Tuesday	0.0230316***	-0.0003212***	0.0071188*	-0.049**	-0.0003*	0.013**	***
Wednesday	0.0135685***	-0.0001332	0.0016792	0.0002	0.0002	-0.002	***
Thursday	0.0196099***	-0.0001200	0.0013883	-0.019+	-0.00003	-0.003	***
Friday	0.0257358***	-0.0001051	0.0008667	-0.014	-0.0002	0.008+	***
Saturday	0.0345133***	0.0001679+	-0.0066123*	-0.034	-0.0005*	0.016**	***
Sunday	0.0129075*	-0.0000765	0.0008931	0.046*	-0.001**	0.019**	***
Note:				+p<0.01; * p <0.05; **p<0.01; ***p<0.001			

For SUV drivers, we observe similar results as illustrated in Table B4. Positive income elasticity is consistently significant throughout the week. Income targeting and inertia are significant from Sundays to Tuesdays. We do observe that time targeting emerges for Thursday to Saturdays, potentially suggesting that drivers may have time goals approaching the weekend. Similar to our original results, we do not find any significant effects nor clear patterns for our key variables in the second stage.

Table B4 Estimates for the day-level two-stage estimation for SUV drivers when weekly targets were reset after at least 2 days of inactivity.

	Stage 1: Work or not?			Stage 2: How long, conditional on working?			
SUV	Offer	ISF	HSF	Earnings	ISF	HSF	IMR
Monday	0.0220245***	-0.0004289***	0.0134450***	-0.016	0.0002+	-0.004	***
Tuesday	0.0114042***	-0.0001390**	0.0029438+	-0.011	0.00004	-0.0005	***
Wednesday	0.0147534***	-0.0000514	0.0000251	-0.010	0.00002	0.001	***
Thursday	0.0253352***	0.0000545	-0.0036865*	-0.020**	0.0002	-0.005	***
Friday	0.0134265***	0.0000535	-0.0031633*	0.003	-0.00003	0.002	***
Saturday	0.0130800**	0.0000678+	-0.0028842*	-0.049*	-0.0001	0.004	***
Sunday	0.0057374	-0.0001126**	0.0038084**	0.007	-0.0002+	0.008+	***
Note:				+p<0.01; * p <0.05; **p<0.01; ***p<0.001			

Appendix C: Competition Among Ride-hailing Platforms

In §4.2.4, we discuss four different metrics to control for unobserved demand for ride-hailing services and competition effects. Our main results presented in §5 include all observations from October 2016 to September 2017, the weather information, and the aggregated number of trips on competing platforms ($NumFHV$) as controls for market conditions. For observations between July and September 2017, we conduct an additional analysis to further include $Speed$ and $AggSurge$ as covariates. These new results are consistent with our main results. Tables C5 and C6 display the estimates for the first stage estimation of whether or not to work for each shift. We observe a generally positive income elasticity, income targeting behavior, and inertia throughout the shifts. Speed appears to have a negative impact on the decision to work in general, suggesting that drivers are less likely to work for the focal platform when there is less traffic. The aggregated surge also has a negative impact on the decision to work. This is to be expected: given that the financial incentive for the focal platform is fixed and known, drivers are less likely to work when the outside option is more appealing.

Table C5 **Estimates for the shift-level first stage estimation for sedan drivers during Summer 2017.**

Sedan	Offer	ISF	HSF	Speed	AggSurge
Mid-day	0.0075***	-0.0354**	3.6385***	-0.0298	-2.9551***
PM peak	-0.0209***	-0.0016*	0.4743***	-0.0536**	-3.9532***
PM off-peak	0.0136***	-0.0034***	0.413***	0.0132	-1.1326**
Late night	0.01079**	-0.004***	0.38036***	-0.07055***	-0.51665
Note:			*p<0.05; **p<0.01; ***p<0.001		

Table C6 **Estimates for the shift-level first stage estimation for SUV drivers during Summer 2017.**

SUV	Offer	ISF	HSF	Speed	AggSurge
Mid-day	0.0035**	-0.0535***	4.3936***	0.0007	-2.5716***
PM peak	-0.0433***	-0.0024***	0.5249***	-0.0563***	-3.6690***
PM off-peak	0.0028	-0.0024***	0.3414***	-0.0121	-0.2124
Late night	0.0085***	-0.0023***	0.2945***	-0.0785***	0.0920
Note:			*p<0.05; **p<0.01; ***p<0.001		

The results for the second stage are relatively consistent as well (see Tables C7 and C8). Higher hourly earnings appear to be associated with a longer work duration for most shifts. Income targeting behavior becomes less significant. Inertia is stronger earlier on in the day. Finally, we observe that, conditional on driving for the shift, drivers are less influenced by the traffic conditions or by the potential surge pricing from other platforms.

Table C7 **Estimates for the shift-level second stage estimation for sedan drivers during Summer 2017.**

Sedan	Earnings	ISF	HSF	Speed	AggSurge	IMR
Mid-day	0.008	-0.019***	1.604***	-0.039	0.0003	***
PM peak	0.025*	-0.001	0.084***	0.012	0.029	***
PM off-peak	0.003	-0.003***	0.006	-0.0001	0.147	***
Late night	0.03***	0.001	-0.071**	0.019	0.11*	***
Note:			*p<0.05; **p<0.01; ***p<0.001			

Table C8 **Estimates for the shift-level second stage estimation for SUV drivers during Summer 2017.**

SUV	Earnings	ISF	HSF	Speed	AggSurge	IMR
Mid-day	-0.001	-0.008	1.819***	-0.034	-1.008	***
PM peak	0.062***	-0.0002	0.245***	-0.053***	-0.421	***
PM off-peak	0.004***	-0.0002*	0.033***	-0.002	-0.027	***
Late night	0.022***	0.0001	0.021	-0.006	0.843	
Note:			*p<0.05; **p<0.01; ***p<0.001			

For the day-level analysis, we find that, in the first stage estimation, positive income elasticity and income targeting behavior became less apparent. Sedan drivers responded positively to the hourly offer from Tuesday to Thursday, whereas SUV drivers did not. The effect of cumulative earnings is generally insignificant, except a sign of income targeting at the end of the week. However, inertia still significant and apparent for most days, Thursday through Sunday for sedan driver, and Wednesday through Sunday for SUV drivers. Lastly, for the second stage estimation, we find no significant estimates for our key variables. This is in line with our original results, which led us to conclude that the decision on the work duration for the day was not determined entirely at the beginning of the day.

Appendix D: Psychological Explanations for Our Main Results

Our main results suggest that workers on our focal platform exhibit different behaviors regarding cumulative earnings and recent work duration. We believe such different behaviors stem from the fact that people perceive the values of time and money differently. Contrary to a common saying that time is money, empirical research from psychology shows that decisions about time follow different rules than decisions about money. For example, Leclerc et al. (1995) finds that people are more averse to uncertainty with time as contrasted with money. In other words, people are risk averse with respect to decisions in the domain of time loss despite being risk-seeking with respect to decisions involving monetary loss. The authors concluded that because time is less substitutable than money, being certain is more important for decisions about time, and people are more averse when there is uncertainty about the allocation of time. Soman (2001) shows that people do not mentally account for their time in the same way as they account for money as the former is more difficult, while Okada and Hoch (2004) demonstrates that people spend time in a systematically different way from when they spend money because the value of time is of greater ambiguity. The distinction of attitude towards time and money applies to work motivation and decisions as well. Workers who can adjust their own work schedules are found to be influenced by internal reference targets. Depending on the context, workers may form only a target for income (Camerer et al. 1997), a target for time (Farber 2015), both in the same direction (Crawford and Meng 2011), or both in the opposite direction as observed in our work. DeVoe and Pfeffer (2007) shows that organizational practices such as how firms pay their employees may influence employees' psychological evaluation of time and the tradeoffs they make between time and money.

Our key insight suggests that gig economy workers may exhibit inertia at work. In our context, inertia refers to the positive correlation between the recent work duration and the decision to start a new work shift. We have identified the following three potential explanations of inertia from the fields of psychology, organizational behavior, and management.

(i) First, inertia could be linked to the concept of the experience of flow from positive psychology. A flow state is the mental state in which a person performing an activity is fully immersed in a feeling of energized focus, full involvement, and enjoyment in the process of the activity (Csikszentmihalyi and Csikszentmihalyi 1992). The complete absorption into the activity affects how the person perceives the sense of time, leading to a continuation of performing the task even though marginal benefit is negligible. Flow theory postulates key conditions required to achieve a flow state. These conditions include clear goals and task structure, clear and immediate performance feedback, a balance between the challenges of the task and one's own skills, one's feeling of control, and one's intrinsic motivation. Gig economy workers are likely to meet these conditions since gig tasks typically have a known set of goals and structure, feedback (e.g., from customers) and compensation are provided frequently, and workers are generally skilled at the particular tasks and have some control over their decisions (e.g., work schedule). Csikszentmihalyi and LeFevre (1989) suggests that flow can be experienced in both work and leisure settings, but more dominantly in the former. Among different leisure activities, the authors find that driving is the most common task that generates the flow experience. This finding fits well with our analysis of ride-hailing drivers. Therefore, it is possible that drivers on the focal platform are more likely to work if they recently worked for a longer duration because they are also more likely to experience the flow state.

(ii) Second, inertia may reflect work addiction caused by stochastic rewards. Applying insights from neuroscience research that stochastic rewards could act as a motivator, Corgnet et al. (2020) conducts a series of behavioral experiments to investigate the relationship between stochastic rewards and workers' likelihood to quit working on effortful tasks. The authors found that participants who were offered a stochastic rate of compensation stayed working for a longer period than those offered a deterministic rate. The persistence on the tasks is linked to stress generated by the uncertainty. In a gig economy setting, compensation to workers is typically determined in response to real-time market conditions (e.g., demand) and depends on the specific task and workers' performance. Work addiction among gig workers has been documented and attributed to the rate of compensation (Kruzman 2017). For our focal platform, financial incentives are decided and communicated to drivers ahead of time, but drivers' opportunity costs (e.g., incentives from competing platforms) are not deterministic. Therefore, it is possible that inertia is related to workaholism driven by uncertain rewards.

(iii) Third, inertia, as the absence of fatigue, could be associated with gig workers' flexibility in deciding work schedule. Watanabe and Yamauchi (2016) shows that when workers voluntarily opted to work for a longer period, there is a positive effect on their work-life balance due to the enjoyment of the work itself or increased rewards. Having control over work duration and being compensated for the work are found to be important for workers' satisfaction. Similarly, workers who voluntarily chose to work overtime did not feel more fatigued but instead felt satisfied as long as they chose their own schedule (Beckers et al. 2008). Although the concept of overtime work can only be applied loosely to gig workers since they have full control of their entire schedule, these findings highlight the potential beneficial impact of the flexibility to choose one's own work schedule: reduced fatigued and increased satisfaction. A study on technical contractors whose schedule were not decided by the organization shows that, despite having full control over their work schedule and perceiving the privileged flexibility, these contractors chose to work long hours and appeared to follow a less flexible schedule (Evans et al. 2004). They considered leisure time as a period of loss without pay and hence they sought to minimize time away from work. Using the British Household Panel Survey, DeVoe et al. (2010) observes that individuals who received hourly wage are more willing to trade their leisure time to work and earn more money than those receiving a salary pay. Putting these findings together, we conclude that in our setting where workers can freely choose their own work schedule and receive hourly pay, workers are more likely to work for a longer period, become more satisfied with long work hours, and feel less fatigue.