The Impact of Economic and Behavioral Drivers on Gig Economy Workers

Motivation: In today’s ever-expanding “gig economy”, independent workers can freely choose when to work as well as seamlessly switch between multiple platforms that offer different incentives. Once a small minority of low-skilled workers with relatively low income, the gig economy now attracts high-skilled workers who are opting to join a flexible workforce. Companies greatly benefit from increased labor flexibility as they can hire workers with different skill levels to work at different times while paying them only for the work they perform. Although the core of gig economy’s success lies in the perfect match between demand and supply, companies need to ensure that their services appeal not only to customers (demand) but also to service providers (supply). This poses an enormous challenge in planning and committing to a service capacity, during both peak hours (when demand is high), and off-peak times when only a handful of workers are needed. How can firms recruit the right number of on-demand workers at the right time? To address this question, it is important to first understand: How do gig workers make working decisions? Our project is in collaboration with a ride-hailing company with the goal to not only improve the way of predicting the number of drivers who will work during a given day and time, but also understand how to better incentivize them, as a way to match supply and demand.

Related Work: The gig economy has become an increasingly active research area that spans several disciplines, from economics to operations management. For decades, economists have been studying how labor supply is affected by wage changes, notably among taxi and, more recently, ride-hailing drivers. Since the seminal work by Camerer et al. (1997) proposed a behavioral model of labor supply and coined “income targeting” for taxi drivers, subsequent studies have drawn different conclusions, even among researchers using data from on-demand platforms. For example, Sheldon (2016) does not find any evidence of income targeting, while Farber (2015) does. Our paper aims to reconcile this argument by exploiting our rich data set that includes a complete description of the supply side. Prior studies have investigated the relationship between wage/income and working hours, but typically do not account for the workers who did not work. By using a two-step method to first predict the working decision, and then the number of hours worked, we address the issue of self-selection bias that arises from the fact that drivers’ decisions are not random. We also propose an operational framework to
help companies design incentives and predict staffing levels. While some operations studies focus on the demand side (e.g., Benjaafar et al. 2015), we focus on the supply side (e.g., Gurvich et al. 2016). Recently, Chen et al. (2017) document how Uber drivers value real-time flexibility and estimate the associated driver surplus, which is significantly higher relative to less flexible arrangements. Using data from a Singaporean taxi company, Kabra et al. (2017) find that driver incentives are more effective than passenger incentives in the long run, and that threshold incentives are more effective relative to linear incentives. Our paper studies the impact of incentives on the workers’ behaviors in the gig economy and develops an operational strategy for capacity planning.

Research Questions and Methodology: Our key research questions are: (i) How do gig economy workers make work decisions? How do they react to incentives? What are the factors that shape each worker’s decision at a particular time? (ii) How can firms design incentives to recruit their workers? We answer these questions by proposing an econometric model to explain workers’ labor decisions. Our data set consists of shift-driver-level financial incentives, and work-related activities from an on-demand ride-hailing platform (from October 2016 to September 2017). It includes several millions driver-shift observations of financial incentives and driving decisions where a given day is divided into 6 shifts. The incentives are composed of an hourly base rate and 3 different types of promotions, for which we have complete information (for all drivers and shifts). The unique feature of our data set is that we observe all incentives offered regardless of whether or not drivers worked for the platform. The availability of non-driving observations allows us to employ a two-stage Heckman estimation method; first to predict the likelihood of a given driver to work during a given shift/day, and second to estimate the number of hours worked. We also incorporate instrumental variables to establish a causal relationship between the driver’s decision and the financial incentives, while controlling for factors such as weather and past work frequencies. To test for potential income and time targeting, we include the accumulated income and number of hours worked on the same day prior to any focal shift. We then compare our model to machine learning techniques that predict workers’ decisions, given the past working history and the financial incentives.

Results: Using a model at the shift level while accounting for drivers’ fixed effects, we find that the financial incentives have a significant positive influence on the decision to drive and on the numbers of hours worked. The former is intuitive as workers react positively (i.e., more likely to drive) to increased wage, while the latter seems counterintuitive as drivers can earn the same amount by driving shorter when offered a higher hourly wage. Interestingly, we observe that the driver’s cumulative earnings and duration (in the same day) have contrasting effects. The number of hours a driver has worked up to now has a significant positive influence on the decision to drive a new shift and on the number of hours
worked. We posit that the former phenomenon could be explained by inertia or momentum (i.e., the tendency to continue working after having worked for some time). The latter phenomenon may seem counterintuitive at first. We also find that the impact of income target appears to be time-dependent. Earlier in the day, the larger amount of money the driver has made during prior shifts, the longer s/he would drive on the next shift. On the other hand, for afternoon and late-night shifts, the influence becomes negative, implying that the driver is more likely to quit driving if s/he has earned more for a long period of time. One possible explanation is the income targeting similar to Camerer et al. (1997): The closer drivers are to their (daily) targets, the shorter the driving period. An additional reason can be the fatigue experienced by the driver after working during prior shifts. Interestingly, drivers seem to rely more on their earnings than on the number of hours worked when deciding when to quit. Replicating our analysis at the day level, we observe that most results remain consistent. As before, the negative impact of income targeting appears later in the week (Thursday-Sunday). Our paper is among the first to provide a rigorous analysis of the complete decision process of gig economy workers who can freely choose whether to work and when to quit. We observe a negative income elasticity as suggested by the behavioral model of labor supply while showing that income targeting is only evident in later shifts of the day and in later days of the week. Further, our results continue to hold when we omit drivers’ fixed effects. We believe that the insights drawn from our model can have a significant impact on real-world practices, particularly on worker’s compensation and staffing decisions.

References


\(^1\)Drivers receive a weekly debrief about the upcoming week on Sunday’s night. Thus, we consider Monday as the first day of their working week.