Change in Online Taxi Drivers' Labor Supply: Experience or Price Effect?*

By Peyman Shahidi†

I quantitatively study the effect of online taxi drivers' subjective belief about goodness of ride prices on their ride acceptance behavior. I develop a continuous-time search model based on two unique ride dispatching characteristics of Tapsi, an Iranian ride-hailing company, whose dataset is being used in a regression discontinuity setup to decompose the effect of exogenous price shocks on drivers' ride acceptance into two components: (1) pure price effect, and (2) experience effect. A discrete-time simulation of the model shows how ride completion histories affects drivers' expectations of future earnings. Results indicate how this decomposition allows us to explain heterogeneous responses to similar ride offers not only from different drivers but also from the same driver at different times.

Extensive research has been done in various fields of economics on measurement of labor supply elasticity. That is, how much a change in wages alters hours of work supplied by the workers. In traditional economic models, agents are assumed to be able to freely shift the level of supplied hours of work in response to wage variations. However, most practical contracts limit proper investigation of true labor supply elasticity as employers tend to require a fixed amount of hours worked by employees with very little (if any) flexibility. Due to this obstacle, environments that provide flexibility in choosing working hours have come to economists' attention. One instance of such environments is the market of ride-hailing services.

I develop a continuous McCall (1970) search model in which drivers decide to accept or reject an offer based on their subjective evaluation of ride proposal based on its characteristics. I show how previous ride fulfillment experiences in different areas affect their ride acceptance through changing reservation wages. Technically, I show that better work conditions in origin(destination) of a trip raises(lowers) drivers' reservation wage. I mode drivers' behavior, utilizing two unique ride matching features adopted by Tapsi, an Iranian ride-hailing company, on its supply side of the market. These features are: (1) full disclosure of trip information to the driver prior to the ride being accepted, and (2) no cost imposed for ride rejection. Together, these characteristics enables me to study the

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† P. Shahidi: University of Chicago Booth School of Business, 5807 S Woodlawn Ave, Chicago, IL 60637. Email: peyman.shahidi@chicagobooth.edu

dynamics of online taxi drivers decision making in their ride acceptance behavior. Stark differences due to small changes in simulations prove the importance of drivers' subjective beliefs about goodness of ride offers. I argue that for estimation of the *true* labor supply elasticity, this channel should be taken into account. More precisely, the effect of an exogenous shock to prices on labor supply must be decomposed into two components: (1) *pure* price effect, and (2) experience effect.

Most prior works on the subject of drivers' labor supply have neglected the experience effect and attributed changes in working hours fully to exogenous changes in prices, thus, biasing the results (sign of the bias is ambiguous and may differ in every case). This lack of proper investigation is mainly due to the difficulty of data collection and identifying this channel. In recent years, with the advent of online ride-hailing companies that collect invaluable data from users, this obstacle has been removed. In traditional taxi markets cabdrivers roamed the streets searching for passengers. However, in ride-hailing platforms drivers and passengers are matched to each other at a much lower cost. This matching system bypasses the inefficiency of traditional taxi services in finding passengers.[1,2] Moreover, tracking each driver's ride choosing patterns has been made easier in these platforms. As a result, the role of experience accumulation (both in the long-term and during a single working shift) can be studied extensively using rich datasets. This allows economists to answer fundamental questions regarding worker behavior that were previously hard to identify.

The rest of the paper is organized as follows. Section I expresses our contribution to literatures surrounding the subject of study in this paper. Section II discusses the institutional backgrounds and characteristics of Tapsi's ride proposals dataset. Section III introduces the model and its implications. Section IV provides simulation results of a simplified version of the model. Section V concludes and points out future research direction.

I. Literature Review

Taxi drivers are more or less able to freely choose their working hours. In their seminal paper, Camerer et al. (1997) investigated daily labor supply elasticity of New York City (NYC) taxi drivers. They showed that in contrast to predictions of neoclassical models, labor supply elasticity can be negative. This finding brought upon the idea of income targeting among taxi drivers. According to this hypothesis, drivers work regardless of fare levels until a predetermined income level is reached. That is, if wages are relatively high during a working shift, drivers leave the market sooner and if wages are relatively low, they work for longer hours. The literature on reference-dependence utilities is vast. However, the empirical

[1]See Buchholz (2015) for search frictions in the traditional taxi service markets.

[2]Fréchette, Lizzeri and Salz (2019) point out the matching frictions as a source of inefficiency in these type of markets.

findings have not shown an accord.[3] A strand of this literature on which I will concentrate in this paper, focuses on working habits of taxi drivers.

Contrary to initial beliefs that income targeting is the main explanatory pattern in drivers' choice, hour targeting seems to have a larger explanatory power in drivers' continuation of working decision, however, the income targeting hypothesis can not be rejected altogether (perhaps because the two are closely related). On one hand, several papers other than Camerer et al. (1997) have supported income-dependence behavior: Chou (2002) and Agarwal et al. (2015) show that Singaporean drivers' working pattern is consistent with income targeting hypothesis and Morgul and Ozbay (2015) obtain the same results for NYC taxi drivers. On the other hand, using a different data sample of NYC yellow cabs and exercising different methods compared to Camerer et al. (1997), Farber (2005) and Farber (2008) indicate that NYC taxi drivers do not entail income targeting behavior. However, both papers show that stopping decision is primarily explained by cumulative working hours. Crawford and Meng (2011) use the same dataset to argue that drivers respect both income and hour targets by estimating a reference-dependence model. The paper shows whichever target is reached later defines the labor supply behavior of drivers. Resolving concerns about the use of incomplete samples in prior works, Farber (2015) ultimately shows little evidence of income targeting by studying the full dataset of NYC cabdrivers between 2009 and 2013. Although, he does show that drivers' shift ending decision is largely explained by their working hours.

Most recently, Thakral and Tô (2017) document evidence from NYC taxi drivers and introduce a new notion of adaptive reference-point models. In extreme cases, their model can accommodate both neoclassical and reference-dependence viewpoints. This paper is close to the work of Thakral and Tô (2017) in the sense that I model drivers as economic agents who update their beliefs about work conditions as they are working. This instant belief adjusting causes heterogeneous ride acceptance patterns from drivers throughout their shifts.

I use a search and matching model similar to conventional job seeking environments to study the tradeoff between accepting and rejecting ride offers. I extend the basic partial job search model of McCall (1970) such that driver's belief about wage distribution changes every time she receives a ride proposal. Therefore, her reservation wage differs not only for offers with distinct characteristics but also for the same offer at different times. The model encompasses learning in terms of updating driver's prior belief about work condition. This is different form approaches found in the literature of search models with learning. The works in that literature mainly use the notion of learning by doing which enables agents

[3] Nguyen and Leung (2013) and Chang and Gross (2014) for instance, show that workers carry out strong reference-dependent preferences in fishing and fruit packing, respectively. In contrast, although Fehr and Goette (2007) show findings consistent with the neoclassical view for bicycle messengers' labor supply in one month horizon, the authors interpret the results such that messengers act according to reference-dependence behavior in shorter horizon of days. Similarly, Oettinger (1999) asserts that the daily labor supply elasticities of stadium vendors is positive.

to increase their productivity and/or sector-specific human capital. In contrast, I implement belief updating into the model with a Kalman filter. The Kalman filter method basically implements a discrete version of Bayesian updating by extracting measurement signals from some observable variables.[4] This approach serves my purpose better as learning in this framework takes place at (discrete) times when the driver is proposed an offer by the platform. In terms of methodology, the closest work to this paper in studies of taxi drivers' working behavior is Chen et al. (2019). This paper uses reservation wage variations quantifying the value of flexibility in working hours. In this paper drives' past ride fulfillment experience is reflected into their future expectations through changing reservation wages. It must be noted that this channel has not been considered in the study of Chen et al. (2019).

Although many studies have been conducted on the subject of taxi drivers' labor supply, little attention has been paid to the effect of experience on their working pattern. In fact, better knowledge regarding where and when to look for passengers helps drivers to extract the most out of their time. A significant part of decision making procedure is attributed to drivers knowing how to choose rides efficiently. Maruthasalam et al. (2018) point out the importance of drivers' strategic behavior in choosing ride offers. The efficacy of experience on drivers' ride fulfilling behavior has been first denoted by Camerer et al. (1997). In this paper, authors showed that inexperienced drivers incorporate negative elasticity of labor supply while experienced ones have almost zero sensitivity to changes in price. Furthermore, Farber (2015) and Haggag, McManus and Paci (2017) show that with accumulation of experience, drivers become more efficient in choosing earning opportunities. In terms of studying the effect of drivers' past experience on ride acceptance, the closest paper to our work is Haggag, McManus and Paci (2017). The authors in that paper show the extent to which NYC cabdrivers learn to find passengers better over time by completing more trips in different areas. In our work, we discuss the channel through which these ride completions enables drivers to choose ride offers more efficiently.

II. Tapsi's Ride Proposals Characteristics

A. Institutional Background

Tapsi is the second largest online ride-hailing platform in Iran. Tapsi's first and largest market is the metropolitan area of Tehran. An important feature of the company that helps identification of driver's ride acceptance behavior is that until November 2018, Tapsi was the only online ride-hailing platform available in Tehran that allowed cars with non-local plate numbers to operate in its market. As a result, by restricting attention to those drivers who were working in Tehran

[4]Interested readers may see Hamilton (1994) and Kim, Nelson et al. (1999) for diverse applications of Kalman filters.

with plate numbers from outside of the city, we resolve concerns about the possibility of drivers simultaneously working in more that one platform. In other words, these drivers were not able to receive competing ride offers and/or get different prices for similar ride offers across different platforms. Therefore, their ride acceptance patterns will not be subject to any biases or misinterpretations of this kind.

Before 22 May 2018, Tapsi offered only one type of transportation service (which later became) known as '*Tapsi Classic*'. In this service, every passenger privately benefits transportation from one location to another. On this date, another type of service, by the name of '*Tapsi Line*', was introduced. In this service, passengers whose destinations happen to be in common routes are able to share their rides for up to 30% lower prices. In this work, we focus on the properties of the *Tapsi Classic* service due to three reasons. First, during the initial running months of *Tapsi Line*, although it was rapidly growing, most of the users were not familiar with it yet. Second, before November 2018, a large portion of drivers were using an old version of the driver's application that was not capable of incorporating rides from *Tapsi Line*. Third, and most importantly, the characteristics of this type of service is not a matter of interest for our study purposes from a theoretical point of view.

B. *Ride Dispatching Mechanism*

The ride dispatching mechanism used by Tapsi at the time of study is described in the next two paragraphs.[5] Passengers are able to observe the price of a certain ride after specifying an origin and a destination on their phone applications at will before submitting a ride request. If they decide to submit a request, the dispatching system offers the ride proposal to the nearest (in terms of pickup ETA) driver. If the nearest driver does not accept the request, the second nearest driver will be considered next and so forth. Drivers are given 15 seconds to decide if they want to accept or reject an offer. If 15 seconds have passed without any responses (acceptance or reaction), the ride offer is considered to be rejected by that driver. It should be noted, however, that before the end of this 15 seconds, the ride proposal will be sent to the next nearest driver. Therefore, most of the times, multiple drivers are simultaneously observing the same ride request. This is for the purpose of reducing passengers' average waiting time as it promotes competition among drivers so that if they do not respond fast enough, the proposal may be seized by another driver. Finally, ride requests will not be sent to drivers with more than 8 minutes pickup ETAs.

This research is mainly motivated by two intriguing features in the dispatching mechanism on the supply side of the market. First, unlike conventional ride-hailing companies such as Uber and Lyft, the drivers operating under Tapsi are

[5]See Erhun Özkan and Amy R. Ward (2020) for properties and efficiency of matching mechanisms used in taxi markets.

informed about every characteristics of the ride offer at the moment they receive a request. Meaning that they are provided with information such as destination location and ride ETA right after the platform has issued them that ride proposal. Thus, drivers are given the opportunity to plan ahead by taking into account hypothetical ride offers when they arrive to the destination. This lets us investigate the effect of information disclosure on drivers' ride acceptance behavior. Second, the platform imposes no penalties (pecuniary or otherwise) to the drivers for rejecting proposals regardless of type of rejection (either manual decline or rejection caused by inaction in the 15 seconds time window). This allows drivers to arbitrarily accept only those ride proposals that fit their personal preferences without fear of punishments. These two unique features enable drivers to strategically decide what rides to fulfill according to their subjective belief about goodness of ride offers so that their revenue is maximized within a working shift. For these reasons, studying the working pattern of agents operating in this market provide a unique opportunity for us to answer fundamental questions regarding worker behavior that were previously hard to identify.

C. *Pricing Mechanism*

The price of each ride in Tapsi is determined by two distinct mechanisms: *baseline pricing* and *surge pricing*. The baseline ride price is a function of distance between origin and destination as well as ride ETA on top of other ride characteristics such as congestion, night hours, weather conditions, etc. Additionally, a fixed fare is added to each ride's price in order to compensate the driver for her internet and/or phone costs of finding the passenger after the ride has been accepted. It must be noted that the price of rides should always be greater than or equal to a lower bound. The corresponding values are different for every city. Tapsi's commission is constant for every ride and equals 15% of the ride price.

An advantage of online ride-hailing companies compared to the traditional taxi services is their ability to adjust supply (of drivers) and demand (of passengers) in real time. The surge pricing mechanism works such that the baseline price of a ride is multiplied by a coefficient greater than 1 in areas with relatively few number of drivers (or equivalently, large number of passengers submitting ride requests). The purpose of this adjustment is twofold. First, it encourages drivers to go to districts with excess demand. Second, passengers tend to submit fewer ride requests on average since the price of each ride has increased. The two effects help the platform to maintain a proper equilibrium level of successful ride dispatches. Similarly, in areas that supply exceeds demand, this mechanism lowers the final price of the ride by applying a surge coefficient lower than 1.[6]

The implementation of surge multipliers is as follows. Initially, a surge-value function maps the excess demand of each district using weighted past 20 minutes'

[6]See Hall, Horton and Knoepfle (2019) for comprehensive examination of this pricing mechanism. Also see Castillo (2020) for welfare effects of surge pricing.

ride requests and number of drivers available into a closed, semi-continuous set of real numbers $[0.8, 2]$.[7] That is:

$$\text{SurgeValue} :\to [0.8, 2].$$

Not surprisingly, this function is strictly increasing(decreasing) with respect to excess demand(supply). Then, using this excess demand/supply and other characteristics Z of the district i, such as city and geographical location within the city, a raw surge coefficient is calculated for every 5 minutes time interval t:

$$\text{RawSurgeCoefficient} = \text{SurgeValue}(\underset{(+)}{Requests_{i,t}}, \underset{(-)}{Available\ Drivers_{i,t}}, Z_{i,t})$$

Then, the raw surge coefficients are rounded to the nearest acceptable surge multiplier according to Table 1.

Table 1—Derivation of surge multipliers using raw surge coefficients. All raw surge coefficients shown in the left column are rounded to the surge multiplier indicated by ★ in the right section. The steps in raw surge coefficients are 0.025. For example, in the fourth row, the set $\{1.1 : (0.025) : 1.275\}$ translates into $\{1.1, 1.125, 1.15, 1.175, 1.2, 1.225, 1.25, 1.275\}$.

	Surge Multiplier							
Raw Surge Coefficients	0.8	0.9	1	1.2	1.4	1.6	1.8	2
$\{0.8, 0.825\}$	★							
$\{0.85, 0.875, 0.9, 0.925, 0.95\}$		★						
$\{0.975, 1, 1.025, 1.05, 1.075\}$			★					
$\{1.1 : (0.025) : 1.275\}$				★				
$\{1.3 : (0.025) : 1.5\}$					★			
$\{1.525 : (0.025) : 1.7\}$						★		
$\{1.725 : (0.025) : 1.9\}$							★	
$\{1.925, 1.95, 1.975, 2\}$								★

III. Model

In this paper, we build on the continuous version of McCall (1970)'s partial search model in a way that it encompasses updating of driver's (subjective) belief about the ride offers' distribution while deciding whether to accept a ride proposal. Denote the set of districts in the city by Y.[8] All the formulas and the mechanisms discussed throughout this section indicate the behavior of one driver.

The setup of the model is as follows. In every district $o \in Y$, each ride proposal's price w is randomly drawn from the distribution of *actual* ride offers at time t,

[7]For practical issues, the weight of the latest 5 minutes is more than the weight of prior 15 minutes at each time. This does not concern our analysis here.

[8]Tapsi groups the geographical area of Tehran into a 16×16 square of 256 districts, i.e. $|Y| = 256$.

day d, and week k.[9] This distribution has a lognormal form:

$$w_{o,kdt} \sim N(\mu_{o,kdt}, \sigma^2),$$

where

$$\mu_{o,kdt} = \mu_{o,kd}(1 + \alpha_{o,kdt}).$$

The mean of ride prices are adjusted for time kdt in district o by the surge multiplier $(1 + \alpha_{o,kdt})$ such that the excess demand/supply is taken into account. Note that the general mean of distribution $\mu_{o,kd}$ may differ in each day of each week, but is constant during the day by assumption. Moreover, each ride offer is randomly assigned a duration $n \in N \subset \mathbb{N}$ and a destination $x \in Y$ from all districts in the city (including the origin of trip). Each proposal sent to a driver by the platform contains the tuple $(w_{o,kdt}, n, x)$ as ride characteristics.

The driver updates her belief about the mean parameter of the wage distribution after observing each offer. The learning process is implemented by the help of a Kalman filter. The reason behind choosing the Kalman filter is twofold. First, it is the best *linear* mean predictor of normal distribution in a learning process. It basically applies the Bayes' rule to the learned parameter in discrete time. Second, it is easy for implementation and simple to work with in modeling procedure. Throughout the learning process, the driver knows the variance parameter of the wage distribution σ^2. She has a prior belief of the mean parameter $\hat{\mu}_{o,kdt} = \mu_{o,kd}(1+\hat{\alpha}_{o,kdt})$. In this work, we assume that the general part of mean parameter $\mu_{o,kd}$ is known (or learned very quickly).[10] Therefore, learning is only restricted to finding the true surge multiplier. The details of belief updating implementation by Kalman filter is discussed in Appendix A.

Following the conventional models in the search and matching literature, whether a driver at time t, day d, week k, and in location o accepts an offer $(w_{o,kdt}, n, x)$ depends on the difference between values of *employment* and *unemployment* states. That is, for each proposal the driver decides whether the ride offer's price $w_{o,kdt}$ exceeds her reservation wage $R^x_{o,kdt}$, a wage that makes the driver indifferent between accepting an offer or rejecting it. Loosely speaking, if the ride characteristics is good enough with respect to driver's expectations $(w_{o,kdt} \geq R^x_{o,kdt})$, she accepts the offer and carries out the trip. Otherwise, if the ride offer is not desirable $(w_{o,kdt} < R^x_{o,kdt})$, she rejects it and waits to receive the next ride proposal. Throughout the process of decision making, the driver updates her belief regarding current area's wage distribution after observing every offer. The timing of decision making is as follows:

1) The driver currently residing in district o receives a ride offer $(w_{o,kdt}, n, x)$.

[9] For notational purposes, natural logarithm of offer prices are shown by w throughout the paper. From hereafter, the words 'wage' and 'price' are interchangeably used in order to denote ride proposals' prices.

[10] This is similar to the reasoning in Haggag, McManus and Paci (2017), where NYC cab drivers quickly adjust themselves to the overall demand conditions of the day.

2) She updates her belief about the mean of the wage distribution in location o at kdt right after observing the offer.

3) If the proposed wage $w_{o,kdt}$ is greater (smaller) than her reservation wage $R^x_{o,kdt}$ for that offer with respect to its characteristics, she accepts (rejects) the ride.

4W) If she has accepted the offer in step (3), she carries out the trip and arrives to the destination x in time n from the start of the trip. (state of employment)

4U) If she has rejected the offer in step (3), she waits for receiving another ride offer in location o. Average waiting time is the inverse of the offer arrival rate in location o, $\frac{1}{\lambda_{o,kdt}}$. (state of unemployment)

5) Back to step (1).

The timeline of accepting/rejecting ride proposals is depicted in Figure 1.

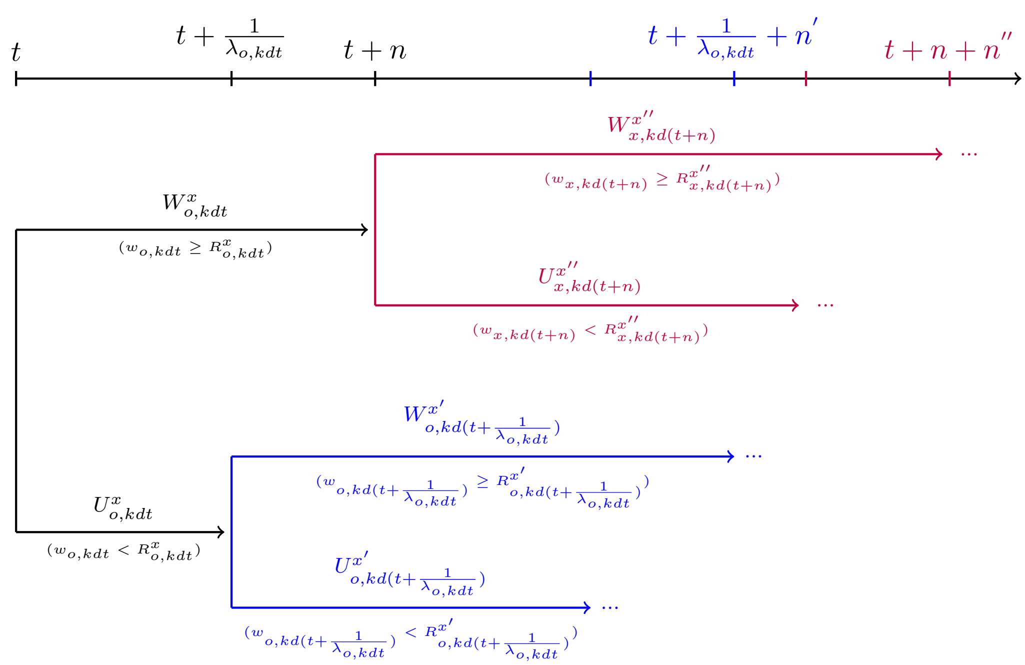

Figure 1. Timing of receiving ride offers during a shift. In the black section, after receiving an offer at t, if the drivers reject her current proposal, she will wait to receive another offer (blue section). In contrast, if she decides to accept the ride, she will arrive to the destination after completion of trip and decides on her next proposal (purple section).

We now mathematically formulate the procedure discussed above. In case she rejects the offer in step (4U), flow value of *unemployment* is given by

$$\delta U(\hat{\mu}_{o,kdt}) = c + \lambda_{o,kdt}\,\mathbb{E}_y[\int_{R^y_{o,kdt}}^{\infty}(1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}))d\tilde{w}], \tag{1}$$

and in case she accepts it in (4W), flow value of *employment* is given by

$$\begin{aligned}\delta W(\hat{\mu}_{x,kd(t+n)}, n, w_{o,kdt}) = \\ \delta n w_{o,kdt} + c + \lambda_{x,kd(t+n)}\,\mathbb{E}_y[\int_{R^y_{x,kd(t+n)}}^{\infty}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w}))d\tilde{w}].\end{aligned} \tag{2}$$

For mathematical details of the derivation procedure see Appendix B. In (1), the flow value of unemployment depends on c, the rate of resting benefits –or waiting cost, depending on its sign– with which the driver receives an instantaneous utility while she is waiting for an offer. Moreover, the rate $\lambda_{o,kdt}$ of offer arrival in driver's current location as well as her belief about its wage distribution $F_{\hat{\mu}_{o,kdt}}$ affects unemployment value. In (2), the flow value of employment depends on the trip duration n and the wage *rate* with which the driver carries the trip. Together, $nw_{o,kdt}$ is the total compensation for completing the ride. Additionally, the rate of resting benefit also adds to employment value since the driver will receive some utility from waiting for her next ride in the destination. Finally, the rate of offer arrival $\lambda_{x,kd(t+n)}$ in destination and driver's belief about its wage distribution at the time of arrival $F_{\hat{\mu}_{x,kd(t+n)}}$ contribute to the flow value of employment. The expectation operator $\mathbb{E}_y$ indicates the uncertainty regarding next offer's destination $y \in Y$. For this reason, the driver calculates the next offer's value with respect to the probability of each possible destination.[11]

With above definitions for employment and unemployment states, the reservation wage $R^x_{o,kdt}$ of a driver residing in district o at time t, day d, week k, for a ride offer with duration n and destination x is given by

$$\begin{aligned}R^x_{o,kdt} = \frac{1}{\delta n}\Big[\lambda_{o,kdt}\,\mathbb{E}_y[\int_{R^y_{o,kdt}}^{\infty}(1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}))d\tilde{w}] \\ - \lambda_{x,kd(t+n)}\,\mathbb{E}_y[\int_{R^y_{x,kd(t+n)}}^{\infty}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w}))d\tilde{w}]\Big].\end{aligned} \tag{3}$$

The following proposition provides the main results of the model.

PROPOSITION 1: *Driver's reservation wage is strictly increasing in mean of current location's wage distribution and strictly decreasing in mean of destination's*

[11] For simplicity in notations and calculations we assume that probability of receiving an offer from every area is the same. We also assume that the expected duration of all future offers are similar, therefore dropping an expectation operator that should have otherwise entered all formulas.

wage distribution at time of arrival. That is: $\frac{dR^x_{o,kdt}}{d\hat{\mu}_{o,kdt}} > 0$ *and* $\frac{dR^x_{o,kdt}}{d\hat{\mu}_{x,kd(t+n)}} < 0$.

See Appendix B.B2 for proof. The analytical formula derived for reservation wage has several implications. First, it indicates that if the driver believes her current location's wage draws are high on average, she expects to receive a high compensation for offers (holding other ride characteristics constant). In turn, her reservation wage will be higher. Second, it shows that if the driver believes wages will be systematically high at the time of arrival to current offer's destination, she expects to have more valuable ride proposals after completion of this trip. As a result, her reservation wage in the residing location will be lower (while evaluating this specific ride proposal) and she will be more likely to accept the offer at hand. Finally, this formula shows that variant beliefs about wage distributions of districts in different times explains volatile ride acceptance behavior towards ride offers with similar prices. This mechanism can largely explain the fluctuation in reservation wage of online taxi drivers throughout their working shifts. Using this characterization, we are able to address why drivers behave differently towards apparently similar (in the sense of having the same prices) ride offers.

The two terms in (3) together, form what we call the 'experience effect' in labor supply decision making of drivers. We add this new notion to the existing '*pure* price effect' which is widely used in the study of labor supply elasticity of economic agents. In this paper we show that changes in hours of work supplied can not be solely attributed to price variations because subjective beliefs about the work conditions affect workers' decision as well. Therefore, for the purpose of estimating *true* labor supply elasticity, drivers' beliefs must be accounted for while exploiting exogenous price shocks. In other words, ride prices are not the only attribute that must be accounted for in studies of drivers labor supply elasticity. This 'experience effect' explains why we observe heterogeneous response to apparently similar ride offers. Using data from Tapsi with its unique ride dispatching features, we can easily estimate the extent that this component affects drivers' decisions. For instance, will drivers have a better sense of wage distributions if they spend more hours working in the streets, or the rate of adjusting beliefs may differ among drivers with more tenure on the job? These are questions that should be studied in future works.[12]

IV. Simulation

A simplified discrete-time version of the model has been simulated.[13] In the simulation environment, there are three districts $y \in Y = \{1, 2, 3\}$ and possible durations for trips is $n \in \{1, 2, 3\}$. For simplicity of calculations, we assume $\bar{n} = 2$ in evaluating durations of future offers by the driver. Also, we drop the week and day indices since they remain unchanged throughout the working shift.

[12]The experience component has been neglected in the work of Chen et al. (2019) that accounts for different sources of reservation wage variation in order to study the value of flexible working hours.

[13]See the previous version for details of the discrete-time model. Available here.

The parameters have been chosen such that the driver carries out only 10 rides in her shift. The *real* wage distributions are constant in all three regions at all times and their *real* surge multipliers are $1 + \alpha = 1 + \alpha_{1,t} = 1 + \alpha_{2,t} = 1 + \alpha_{3,t} = 1.4$. We have assumed that driver knows the general mean parameter $\mu_{i,t}$ throughout the shift and learning only affects beliefs about the surge multiplier. The beliefs are normalized to the general mean parameter such that only the surge multiplier components are shown. We assume that driver's initial belief about the mean parameters is as follows:

$$\hat{\mu}_1 = 2, \qquad \hat{\mu}_2 = 1.4, \qquad \hat{\mu}_3 = 0.8.$$

The variation in reservation wage due to belief updating is shown by the black solid line in Figure 2. In this run the driver is initially residing in region 2 with $\hat{\mu}_2 = 1.4$. She receives her first ride proposal in period 1. This offer is rejected since her reservation wage for that offer exceeds ride offer's price. The shaded area in the lower panel indicates that she has entered state of unemployment and has spent 1 period in it. She then receives another ride offer in period 2. This time the ride characteristics are good enough and she accepts the offer. In the course of ride fulfillment, accumulated earning increases and the reservation wage remains constant. Arriving to the previous trip's destination, she receives another proposal now in region 3. Before she evaluates her reservation wage she updates her belief about current location's surge multiplier after observing the offer's price. In the figure, this is indicated by the change in her belief of area 3, shown by the dashed green line. She then continues to accept ride offers until she reaches the pre-specified count of 10 accepted rides for this working shift.

The evolution of driver's belief about different areas' wage distribution is evident by looking at the three dashed lines in the upper panel of Figure 2. It is because of this phenomenon that reservation wage tends to change during the driver's working shift. It can be seen that the driver displays very different reservation wages for seemingly identical ride offers. We say seemingly identical because it is largely believed that drivers supposedly evaluate ride offers solely by looking at their prices. However, our results indicate that another important factor, namely the subjective belief of drivers about different areas' wage draws, must be taken into account while studying ride acceptance behavior. This factor can explain heterogeneous responses to ride offers not only from different drivers but also from the same driver at different times. In Appendix C we investigated the driver's ride acceptance pattern in cases where she starts her shift from region 1 with $\hat{\mu}_1 = 2$ and region 3 with $\hat{\mu}_3 = 0.8$, in Figure C1 and Figure C2 respectively. The sharp difference in reservation wage evolutions and working patterns during each shift is another proof for the sizable effect of driver's belief about her work conditions.

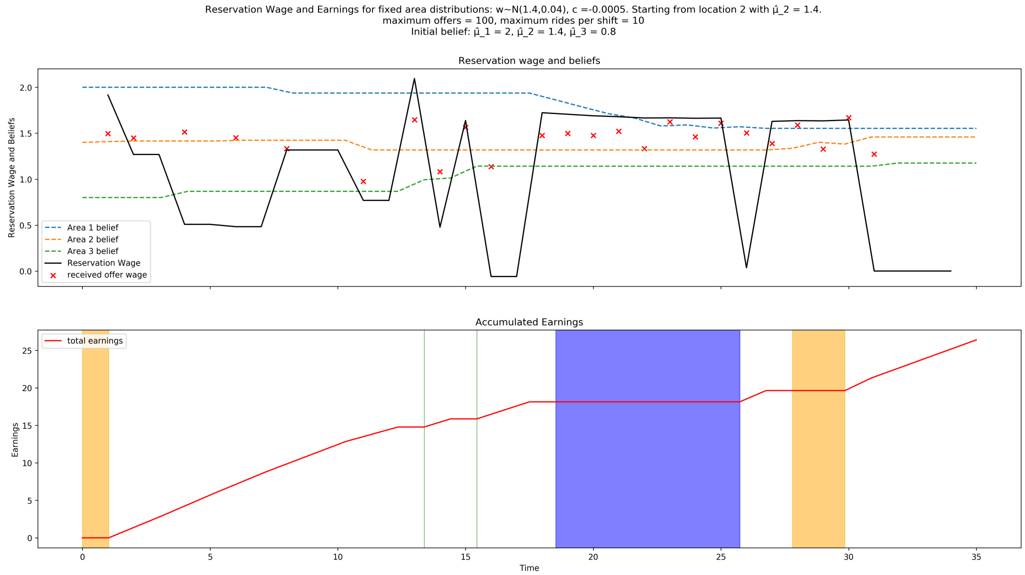

FIGURE 2. SIMULATION OF RIDE ACCEPTANCE PATTERN FOR DRIVER STARTING FROM REGION 2 WITH $\hat{m}u_2 = 1.4$. OBSERVING RIDE PROPOSALS, SHE UPDATE HER BELIEFS OF DIFFERENT AREAS' WAGE DISTRIBUTIONS THROUGHOUT HER SHIFT. SHADED AREAS IN THE LOWER PANEL INDICATE BEING IN STATE OF UNEMPLOYMENT. (THE DRIVER IS FORCED TO TARGET FULFILLING 10 RIDES AT MOST. INSTANTANEOUS RATE OF RESTING BENEFIT (OR COST OF REJECTION/WAITING) IS $c = -0.0005$ AND REAL WAGE DISTRIBUTION FOR ALL THREE REGIONS IS $N(1.4, 0.04)$. THE KALMAN FILTER PARAMETERS ARE: $Q = 10$, $E = 100$.)

V. Conclusion

This paper examined the effect of drivers' past ride fulfillment experience on their working pattern in a search and matching framework. Drivers in our model are able to strategically choose which offers to accept, a characteristic that resembles the environment of Tapsi. We show that reservation wage depends on driver's belief about mean of wage distribution in trip's origin and destination. An increase in the former increases reservation wage whereas an increase in the latter decreases ride acceptance threshold. Simulations show the importance of this effect on driver's reservation wage and thus, her working behavior. Our results indicate that since drivers evaluate ride offers according to their previous experience, they react differently to apparently similar (in terms of prices) ride offers. This can explain the heterogeneity in ride acceptance among drivers and for the same driver at different times.

Our research provides an opportunity to study many aspects of online taxi drivers' labor supply. Mainly, we will be able to decompose the effect of an exogenous change in prices into two different components. First, a pure price effect and second, a subjective belief term that shows drivers' expectations. We call this second term the 'experience effect'. This channel has been largely neglected in previous studies of labor supply elasticity, causing bias in estimations. In future works, using a methodology similar to that of Chen and Sheldon (2015), we can estimate the labor supply elasticity of Tapsi's drivers as the model has been developed such that it matches features of this online ride-hailing company.

In further extensions, due to our model's flexibility, we will be able to study other aspects of drivers' ride acceptance patterns, including how experience accumulation affect their earnings over time. Furthermore, we are able to estimate the ride acceptance probability of drivers in order to investigate whether online taxi drivers behave according to the reference-dependence hypothesis or the neoclassical view discussed in previous works. This behavior can be quantitatively measured for (perhaps different types of) drivers present in this market. Such empirical works will be done in future studies of drivers' labor supply.

References

Agarwal, Sumit, Mi Diao, Jessica Pan, and Tien Foo Sing. 2015. "Are Singaporean Cabdrivers Target Earners?" *Available at SSRN 2338476.*

Buchholz, Nicholas. 2015. "Spatial equilibrium, search frictions and efficient regulation in the taxi industry." *Working paper, Tech. Rep.*

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler. 1997. "Labor supply of New York City cabdrivers: One day at a time." *The Quarterly Journal of Economics*, 112(2): 407–441.

Castillo, Juan Camilo. 2020. "Who Benefits from Surge Pricing?" *Available at SSRN 3245533.*

Chang, Tom, and Tal Gross. 2014. "How many pears would a pear packer pack if a pear packer could pack pears at quasi-exogenously varying piece rates?" *Journal of Economic Behavior & Organization*, 99: 1–17.

Chen, M Keith, and Michael Sheldon. 2015. "Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform." *UCLA Anderson. URL: https://www. anderson. ucla. edu.*

Chen, M Keith, Peter E Rossi, Judith A Chevalier, and Emily Oehlsen. 2019. "The value of flexible work: Evidence from Uber drivers." *Journal of Political Economy*, 127(6): 2735–2794.

Chou, Yuan K. 2002. "Testing alternative models of labour supply: Evidence from taxi drivers in Singapore." *The Singapore Economic Review*, 47(01): 17–47.

Crawford, Vincent P, and Juanjuan Meng. 2011. "New York City cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income." *American Economic Review*, 101(5): 1912–32.

Farber, Henry S. 2005. "Is tomorrow another day? The labor supply of New York City cabdrivers." *Journal of political Economy*, 113(1): 46–82.

Farber, Henry S. 2008. "Reference-dependent preferences and labor supply: The case of New York City taxi drivers." *American Economic Review*, 98(3): 1069–82.

Farber, Henry S. 2015. "Why you can't find a taxi in the rain and other labor supply lessons from cab drivers." *The Quarterly Journal of Economics*, 130(4): 1975–2026.

Fehr, Ernst, and Lorenz Goette. 2007. "Do workers work more if wages are high? Evidence from a randomized field experiment." *American Economic Review*, 97(1): 298–317.

Fréchette, Guillaume R., Alessandro Lizzeri, and Tobias Salz. 2019. "Frictions in a Competitive, Regulated Market: Evidence from Taxis." *American Economic Review*, 109(8): 2954–92.

Haggag, Kareem, Brian McManus, and Giovanni Paci. 2017. "Learning by driving: Productivity improvements by new york city taxi drivers." *American Economic Journal: Applied Economics*, 9(1): 70–95.

Hall, Jonathan V, John J Horton, and Daniel T Knoepfle. 2019. "Pricing efficiently in designed markets: The case of ride-sharing." *New York University, New York.*

Hamilton, James D. 1994. *Time series analysis.* Vol. 2, Princeton New Jersey.

Kim, Chang-Jin, Charles R Nelson, et al. 1999. "State-space models with regime switching: classical and Gibbs-sampling approaches with applications." *MIT Press Books*, 1.

Maruthasalam, Ponnachiyur, Arulanantha Prabu, Debjit Roy, and Prahalad Venkateshan. 2018. "Refuse or Accept?: Analysis of Taxi Driver Operating Strategies in E-Hailing Platforms." *(July 29, 2018), Available at SSRN: https://ssrn.com/abstract=3294519.*

McCall, John Joseph. 1970. "Economics of information and job search." *The Quarterly Journal of Economics*, 113–126.

Morgul, Ender Faruk, and Kaan Ozbay. 2015. "Revisiting labor supply of new york city taxi drivers: Empirical evidence from large-scale taxi data." Vol. 15.

Nguyen, Quang, and Pingsun Leung. 2013. "Revenue targeting in fisheries." *Environment and Development Economics*, 18(5): 559–575.

Oettinger, Gerald S. 1999. "An empirical analysis of the daily labor supply of stadium venors." *Journal of Political Economy*, 107(2): 360–392.
ΩÖzkan and Ward

Özkan, Erhun, and Amy R. Ward. 2020. "Dynamic Matching for Real-Time Ride Sharing." *Stochastic Systems*, 10(1): 29–70.

Thakral, Neil, and Linh T Tô. 2017. "Daily labor supply and adaptive reference points." *Unpublished manuscript.*

Belief Updating Implementation via Kalman Filter Method

Suppose that the mean of the wage distribution in district o, day d, week k, and time t is the state variable and evolves from time t to time $t+1$ according to (A1) in which $q_{kdt} \sim N(0, Q)$ denotes the randomness of the mean from one period to the next. Driver receives a measurement signal which helps to correct her assessment regarding the mean of wage distribution according to (A2), however, this signal is not accurate and has noise $e_{kdt} \sim N(0, E)$.

$$\mu_{o,kd}(1 + \alpha_{o,kd(t+1)}) = A_{kdt}\ \mu_{o,kd}(1 + \alpha_{o,kdt}) + q_{kd(t+1)} \tag{A1}$$

$$w_{o,kdt} = H_{kdt}\ \mu_{o,kd}(1 + \alpha_{o,kdt}) + e_{kdt} \tag{A2}$$

In the simplest possible case, we assume that the coefficients $A_{kdt} = H_{kdt} = 1$. This means that drivers take the received wage offer as a representation of mean of wage distribution. Moreover, the received wage offer is assumed to be a representative of the mean of the distribution. Note that in this characterization, drivers' belief regarding the mean parameter of the normal distribution has a normal distribution for itself.

Define *'updating rule'* as the dependence form of beliefs. For instance, a driver is able to update her belief during every shift after observing ride offers. Or she can have an assumption regarding a particular block of time (for example, an hour) in a certain day of the week and compare the changes in this time and location with that of the previous week's. In this version of the paper, we assume drivers start in each working area from their latest belief in the previous week $k-1$, and update it during a shift while receiving offers at different times (t, $t+1$, $t+2$, etc.).

The process of learning in a Kalman filter takes place in two steps: *updating* and *predicting*. In the *updating* phase, driver uses the measurement signal, here the received wage offer, to update her prior according to

$$\begin{aligned} \hat{\mu}'_{o,kdt} &= \hat{\mu}_{o,kd(t-1)}, \\ P'_{o,kdt} &= P_{o,kd(t-1)} + Q. \end{aligned} \tag{A3}$$

where $\hat{\mu}_{o,kd(t-1)}$ is the prior of the driver regarding the mean parameter derived in the previous step, and $\hat{\mu}'_{o,kdt}$ is the updated belief regarding the mean parameter for this week. Additionally, $P'_{o,kdt}$ and $P_{o,kd(t-1)}$ are updated variance and prior variance regarding the mean parameter, respectively. In the *predicting* phase of the Kalman filter, driver uses the updated belief derived by observing the wage offer to predict the mean parameter according to

$$\hat{\mu}_{o,kdt} = \hat{\mu}'_{o,kdt} + K_{o,kdt}(w_{o,kdt} - \hat{\mu}'_{o,kdt}), \tag{A4}$$

$$K_{o,kdt} = \frac{P'_{o,kdt}}{P'_{o,kdt} + E}, \tag{A5}$$

$$P_{o,kdt} = P'_{o,kdt}(1 - K_{o,kdt}).$$

where $K_{o,kdt}$ is the Kalman gain. It optimally determines the weight of the measurement and how it should be accounted for in the learning process (it is optimal in the sense that the mean squared error of prediction will be minimized.). The Kalman gain formula (A5) says that the higher the measurement error, E, is, the lower the effect of measurement signal on the predicted parameter in that specific step will be. High measurement error indicates that the measured signal has little information. Conversely, low measurement error indicates that the received measurement signal obtains a lot of information regarding the parameter to be learned. The learning process and the effect of measurement error has been shown in Figure A1. Define *Half-Life* to be the number of periods it takes for the

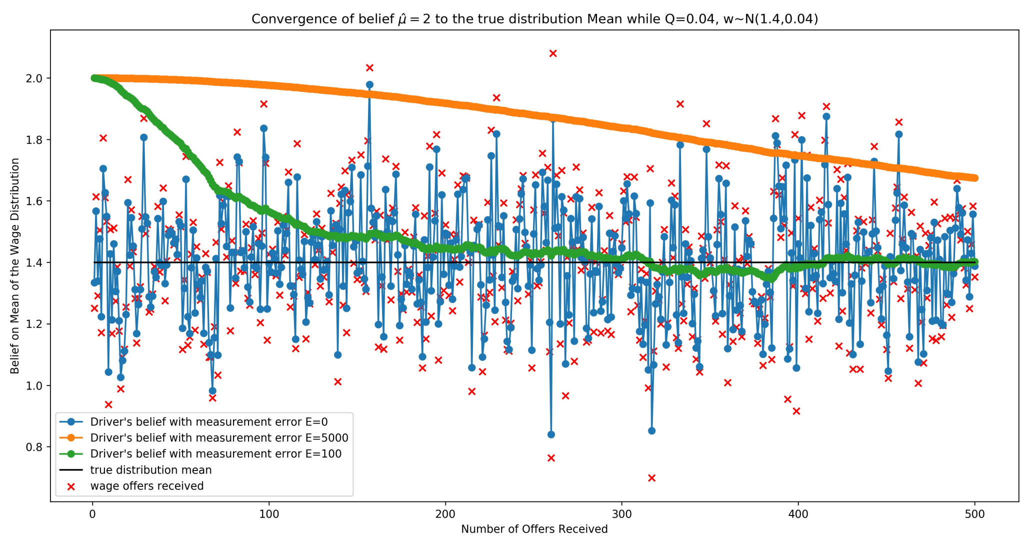

FIGURE A1. EFFECT OF MEASUREMENT ERROR ON BELIEF CONVERGENCE. THE DRIVER STARTS WITH PRIOR $\hat{\mu}_{o,kdt} = 2$, $P = 0.04$ AND THE REAL WAGE DISTRIBUTION IS $N(1.4, 0.04)$. THE PARAMETERS OF THE KALMAN FILTER ARE AS FOLLOWS: $A = H = 1$, $Q = 0.04$.

prior to cover half of the difference between the initial value and the actual mean parameter. This measure shows how fast the converges happens in this context. The difference in learning process for different values of the measurement error is shown in Figure A2.

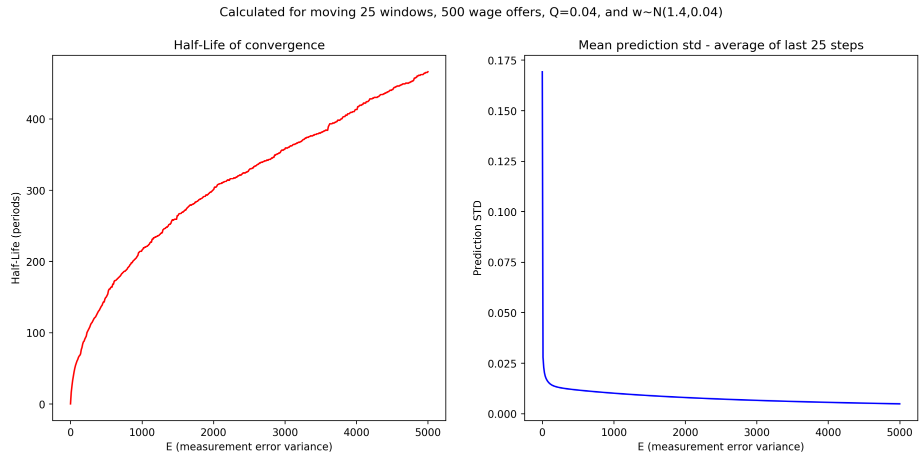

FIGURE A2. THE SEVERITY OF MEASUREMENT ERROR EFFECT ON BELIEF CONVERGENCE. LEFT FIGURE SHOWS THE EFFECT OF MEASUREMENT NOISE IN CONVERGENCE SPEED OF BELIEF. RIGHT FIGURE SHOWS DEPENDENCE OF THE AVERAGE MOVING WINDOW OF PREDICTION STANDARD DEVIATION ON MEASUREMENT ERROR. THE DRIVER STARTS WITH PRIOR $\hat{\mu}_{o,kdt} = 2$, $P = 0.04$ AND THE REAL WAGE DISTRIBUTION IS $N(1.4, 0.04)$. THE PARAMETERS OF THE KALMAN FILTER ARE AS FOLLOWS: $A = H = 1$, $Q = 0.04$.

DERIVATION OF EMPLOYMENT AND UNEMPLOYMENT STATE VALUES, AND RESERVATION WAGE FORMULA

B1. Employment and Unemployment State Values

While unemployed, the driver enjoys an instantaneous utility with rate c. Waiting for the next ride proposal, she expects to receive an offer with Poisson rate $\lambda_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}$ at $\frac{1}{\lambda_{o,kdt}}$ from t. Note that $\frac{1}{\lambda_{o,kdt}}$ is the average time it takes to being exposed to the next offer in the Poisson process. Furthermore, the driver discounts the future with rate δ. It should be noted that δ is very close to 0 as we are studying wages of a single shift. However, its existence is necessary for a closed form solution to exist. We can write

$$U(\hat{\mu}_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}) = cdt + (1 - \lambda_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}dt - \delta dt)U(\hat{\mu}_{o,kd(t+\frac{1}{\lambda_{o,kdt}}+\frac{1}{\lambda_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}})})$$
$$+\lambda_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}dt\,\mathbb{E}_y[\mathbb{E}_{\hat{\mu}_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}}[max\{W(\hat{\mu}_{y,kd(t+\bar{n})}, \bar{n}, \tilde{w}_{o,kdt}), U(\hat{\mu}_{o,kdt})\}]],$$

where the second term shows the case in which the driver has not received an offer and thus, remains unemployed. The third term indicates the rational choice of driver with regard to accepting or rejecting an offer. With her belief at the time of decision making if the employment's value is greater she will carry the trip. Otherwise, she rejects it and waits for the next proposal. The expectation operator $\mathbb{E}_{\hat{\mu}_{i,kdt}}$ indicates that driver calculates the value of receiving an offer with respect to her current belief regarding the mean of wage distribution, constructed according to her updating rule, at kdt in location $i \in Y$. Moreover, the expectation operator $\mathbb{E}_y$ shows that the driver accounts for every possible offer destination (for her next proposal) at each time.

Since she is updating her belief according to Bayes' rule, her best guess regarding $\hat{\mu}_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}$ and $\hat{\mu}_{o,kd(t+\frac{1}{\lambda_{o,kdt}}+\frac{1}{\lambda_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}})}$ is $\hat{\mu}_{o,kdt}$. Similarly, her best guess for the rate of offer arrival $\lambda_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}$ is $\lambda_{o,kdt}$. Therefore, the previous equation reduces to

$$\delta U(\hat{\mu}_{o,kdt}) = c + \lambda_{o,kdt}\, \mathbb{E}_y[\mathbb{E}_{\hat{\mu}_{o,kdt}}[J(\hat{\mu}_{o,kdt}, \hat{\mu}_{y,kd(t+\bar{n})}, \bar{n}, \tilde{w}_{o,kdt})]]$$

where

$$J(\hat{\mu}_{o,kdt}, \hat{\mu}_{y,kd(t+\bar{n})}, \bar{n}, \tilde{w}_{o,kdt}) = max\{W(\hat{\mu}_{y,kd(t+\bar{n})}, \bar{n}, \tilde{w}_{o,kdt}) - U(\hat{\mu}_{o,kdt}), 0\}. \tag{B1}$$

Since employment value (discussed below) is strictly increasing in wage , the driver has a cutoff strategy above which all of the offers will be accepted. The value of this cutoff is called the reservation wage. By simplifying the inner expectation in the previous equation for the unemployment value we obtain

$$\delta U(\hat{\mu}_{o,kdt}) = c + \lambda_{o,kdt}\, \mathbb{E}_y[\int_{R^y_{o,kdt}}^{\infty} (1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}))d\tilde{w}] \tag{B2}$$

where $R^y_{o,kdt}$ is the reservation wage of the driver who has received an offer in district o with destination y and length $\bar{n}$ at kdt. $F_{\hat{\mu}_{o,kdt}}(w)$ is the wage distribution constructed by driver's subjective belief in area o at kdt. Note that in calculating the expected value of having an offer, driver's best guess regarding the duration of next trips is $\bar{n}$. This assumption has been made only for simplicity and does not change the implications of the model. Have we not did so, another expectation must have been taken over all trip durations in every step.

Similarly, the value of accepting a ride proposal with certain characteristics —that is, being employmed —depends on the wage offer at hand, the destination wage distribution characteristics, length of the trip n, and the offer proposal rate in destination at time of arrival. We can write

$$\begin{aligned} W(\hat{\mu}_{x,kd(t+n)}, n, w_{o,kdt}) &= nw_{o,kdt} + (1 - \lambda_{x,kd(t+n)}dt - n\delta dt)U(\hat{\mu}_{x,kd(t+n)}) \\ &+ \lambda_{x,kd(t+n)}dt\, \mathbb{E}_y[\mathbb{E}_{\hat{\mu}_{x,kd(t+n)}}[max\{W(\hat{\mu}_{y,kd(t+n+\bar{n})}, \bar{n}, \tilde{w}_{x,kd(t+n)}), U(\hat{\mu}_{x,kd(t+n)})\}]]. \end{aligned}$$

Substituting for $U(\hat{\mu}_{x,kd(t+n)})$ using (B2), we can write

$$\delta W(\hat{\mu}_{x,kd(t+n)}, n, w_{o,kdt}) = \delta n w_{o,kdt} + (1 - n\delta dt)c$$
$$+\lambda_{x,kd(t+n)}(1-(n-1)\delta dt)\, \mathbb{E}_y[\mathbb{E}_{\hat{\mu}_{x,kd(t+n)}}[J(\hat{\mu}_{x,kd(t+n)}, \hat{\mu}_{y,kd(t+n+\bar{n})}, \tilde{w}_{x,kd(t+n)})]].$$

Again, simplifying the inner expectation in the previous equation and we obtain

$$\delta W(\hat{\mu}_{x,kd(t+n)}, n, w_{o,kdt}) = \delta n w_{o,kdt} + c + \lambda_{x,kd(t+n)}\, \mathbb{E}_y[\int_{R^y_{x,kd(t+n)}}^{\infty} (1 - F_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w}))d\tilde{w}]. \tag{B3}$$

B2. Reservation Wage

With above definitions for values of employment and unemployment states, the reservation wage of driver, $R^x_{o,kdt}$, at time t, day d, week k, currently residing in district o with ride offer duration n and destination x can be calculated from

$$W(\hat{\mu}_{x,kd(t+n)}, n, R^x_{o,kdt}) = U(\hat{\mu}_{o,kdt})$$

which yields

$$R^x_{o,kdt} = \frac{1}{\delta n}\Bigg[\lambda_{o,kdt}\, \mathbb{E}_y[\int_{R^y_{o,kdt}}^{\infty} (1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}))d\tilde{w}] - \lambda_{x,kd(t+n)}\, \mathbb{E}_y[\int_{R^y_{x,kd(t+n)}}^{\infty} (1 - F_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w}))d\tilde{w}]\Bigg]. \tag{B4}$$

Thus, the reservation wage consists of two different terms which together form the '*experience* effect' components. Now, we can calculate the changes in the reservation wage due to changes in two parameters of interest.

PROOF OF PROPOSITION 1:

First, for the subjective belief about the mean of wage distribution in current location, o, we can write:

$$\begin{aligned}\frac{dR^x_{o,kdt}}{d\hat{\mu}_{o,kdt}} &= \frac{\lambda_{o,kdt}}{\delta n}\pi^o\Bigg[-\frac{dR^x_{o,kdt}}{d\hat{\mu}_{o,kdt}}(1 - F_{\hat{\mu}_{o,kdt}}(R^x_{o,kdt})) + \frac{1}{\sigma}\int_{R^x_{o,kdt}}^{\infty} f_{\hat{\mu}_{o,kdt}}(\tilde{w})d\tilde{w}\Bigg] \\ &= \frac{\lambda_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}}{\delta n}(1 - F_{\hat{\mu}_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}}(R^x_{o,kdt}))\pi^o\Bigg[-\frac{dR^x_{o,kdt}}{d\hat{\mu}_{o,kd(t+\frac{1}{\lambda_{o,kdt}})}} + \frac{1}{\sigma}\Bigg],\end{aligned}$$

where π^o is the probability that an offer's destination is in region $o \in Y$. Thus,

$$\text{(B5)} \qquad \frac{dR^x_{o,kdt}}{d\hat{\mu}_{o,kdt}} = \frac{\pi^o}{\sigma} \frac{\frac{\lambda_{o,kdt}}{\delta n}(1 - F_{\hat{\mu}_{o,kdt}}(R^x_{o,kdt}))}{1 + \frac{\lambda_{o,kdt}}{\delta n}(1 - F_{\hat{\mu}_{o,kdt}}(R^x_{o,kdt}))} > 0.$$

Second, for the subjective belief about the mean of wage distribution in the destination, x, of current offer at time of arrival, $t+n$, we have

$$\begin{aligned}\frac{dR^x_{o,kdt}}{d\hat{\mu}_{x,kd(t+n)}} =& \frac{\lambda_{x,kd(t+n)}}{\delta n}\pi^x \Bigg[- \frac{dR^x_{x,kdt}}{d\hat{\mu}_{x,kd(t+n)}}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{o,kdt})) \\ & + \frac{1}{\sigma}\int_{R^x_{x,kdt}}^{\infty} f_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w})d\tilde{w}\Bigg]\end{aligned}$$

Substituting for $\frac{dR^x_{x,kdt}}{d\hat{\mu}_{x,kd(t+n)}}$ using (B5), we can write

$$\begin{aligned}\frac{dR^x_{o,kdt}}{d\hat{\mu}_{x,kd(t+n)}} =& \frac{\lambda_{x,kd(t+n)}}{\delta n}\pi^x \Bigg[\frac{1}{\sigma}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt})) \\ & - \frac{1}{\sigma}\frac{\frac{\lambda_{x,kd(t+n)}}{\delta}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt}))^2}{1 + \frac{\lambda_{x,kd(t+n)}}{\delta}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt}))}\Bigg] \\ =& \frac{1}{\sigma}\frac{\lambda_{x,kd(t+n)}}{\delta n}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt}))\pi^x \times \\ & \Bigg[1 - \frac{\frac{\lambda_{x,kd(t+n)}}{\delta}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt}))}{1 + \frac{\lambda_{x,kd(t+n)}}{\delta}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt}))}\Bigg].\end{aligned}$$

Therefore,

$$\text{(B6)} \qquad \frac{dR^x_{o,kdt}}{d\hat{\mu}_{x,kd(t+n)}} = -\frac{\pi^x}{\sigma}\frac{\frac{\lambda_{x,kd(t+n)}}{\delta n}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt}))}{1 + \frac{\lambda_{x,kd(t+x)}}{\delta n}(1 - F_{\hat{\mu}_{x,kd(t+n)}}(R^x_{x,kdt}))} < 0.$$

The two formulas (B5) and (B6) prove Proposition 1.

Simulation Figures

The setup and environment of these simulation runs are exactly the same as those in Figure 2. Note that the ride offer prices with which she is faced (if not missed because of ride fulfillment) are exactly the same in all figures. Though, trip destinations vary and are randomly assigned to ride offers in each case.

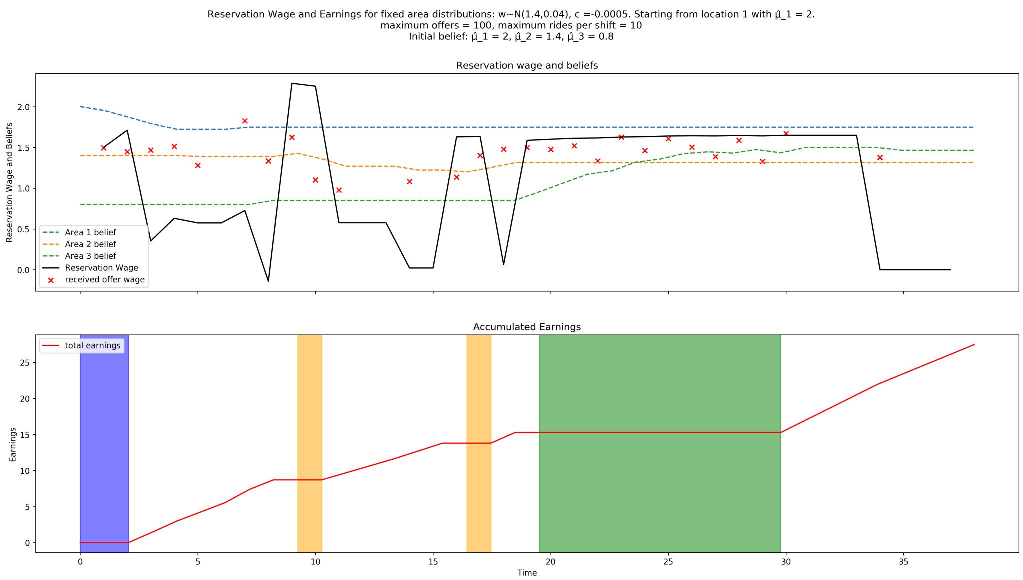

Figure C1. Simulation of ride acceptance pattern for driver starting from region 1 with $\hat{mu}_1 = 2$. Observing ride proposals, she update her beliefs of different areas' wage distributions throughout her shift. Shaded areas in the lower panel indicate being in state of unemployment. (The driver is forced to target fulfilling 10 rides at most. Instantaneous rate of resting benefit (or cost of rejection/waiting) is $c = -0.0005$ and real wage distribution for all three regions is $N(1.4, 0.04)$. The Kalman filter parameters are: $Q = 10$, $E = 100$.)

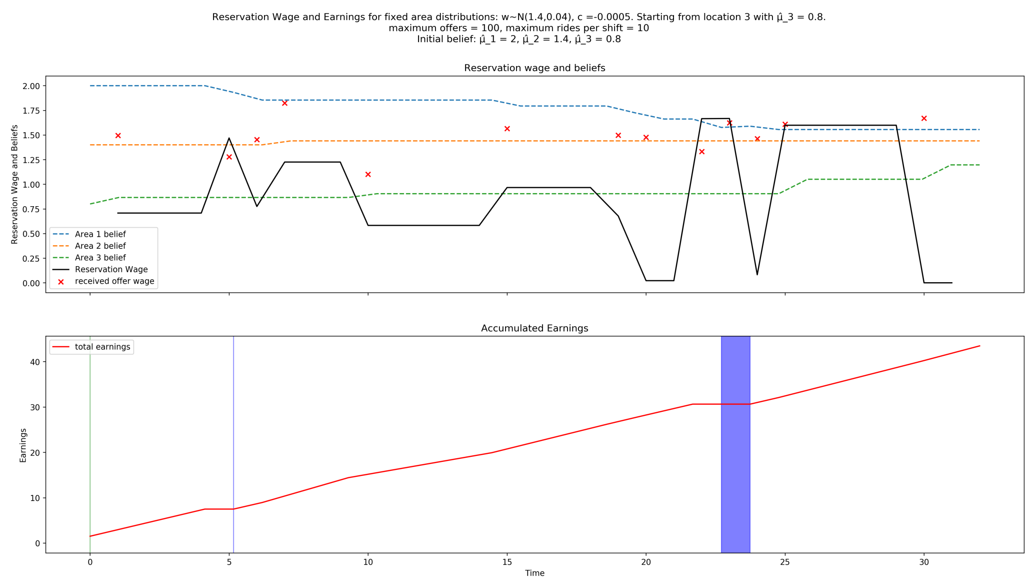

Figure C2. Simulation of ride acceptance pattern for driver starting from region 3 with $\hat{mu}_3 = 0.8$. Observing ride proposals, she update her beliefs of different areas' wage distributions throughout her shift. Shaded areas in the lower panel indicate being in state of unemployment. (The driver is forced to target fulfilling 10 rides at most. Instantaneous rate of resting benefit (or cost of rejection/waiting) is $c = -0.0005$ and real wage distribution for all three regions is $N(1.4, 0.04)$. The Kalman filter parameters are: $Q = 10$, $E = 100$.)