A Behavioral Investigation of Workers' Relocation in On-Demand Platforms

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Abstract

Problem Definition: We have witnessed a rapid rise of on-demand platforms, such as Uber, in the past few years. While these platforms allow workers to choose their own working hours, they have limited leverage in maintaining availability of workers within a region. As such, platforms often implement various policies, including offering financial incentives and/or communicating customer demand to workers in order to direct more workers to regions with shortage in supply. This research examines how behavioral biases such as regret aversion and ignorance of suggestion may influence workers' relocation decisions and ultimately system performance.
Academic/Practical Relevance: Studies on on-demand platforms often assume that workers are rational agents who make optimal decisions. This research investigates workers' relocation decisions from a behavioral perspective. A deeper understanding of workers' behavioral biases and their causes will help on-demand platforms design appropriate policies to increase their own profit, worker surplus, and the overall efficiency of matching supply with demand.
Methodology: We use a combination of behavioral modeling and controlled lab experiments. We develop analytical models incorporating behavioral factors to produce theoretical predictions, which are tested and verified via a series of controlled lab experiments.
Results: We find that regret aversion and ignorance of suggestion are the two major behavioral factors that influence workers' relocation decisions. Regret averse workers are more willing to relocate to the supply-shortage zone than rational workers. Sharing demand information is a better way of communicating customer demand compared with providing suggested actions, since workers often ignore such suggestions due to their inability to perform demand update. In addition, the platform may also need to offer extra financial payment to compensate for workers' relocation cost. Finally, workers' regret averse behavior may lead to an increased profit for the platform, a higher surplus for the workers, and an improved demand-supply matching efficiency, thus benefiting the entire on-demand system.
Managerial Implications: Our research emphasizes the importance and necessity of incorporating workers' behavioral biases into the policy design of on-demand platforms. Policies without considering the behavioral aspect of workers' decision may lead to lost profit for the platform and reduced welfare for workers and customers, which may ultimately hurt the on-demand business.

Keywords: Behavioral Operations; Experiments; Incentives and Contracting; Operations Strategy, Service Operations

1 Introduction

With the advance of information technology, we have witnessed a rapid rise of sharing economy and on-demand sharing platforms in the last few years. Uber, for example, quickly grew to 700,000 active drivers in the United States, nearly three times the number of taxi drivers and chauffeurs in 2014 (Hall and Krueger 2016). It has been estimated that the number of independent workers will reach 40 percent of the US workforce by 2020 (Intuit 2010). These on-demand platforms allow customers to request service in real-time and workers to decide when and how much to work without being bounded by any specific work arrangements.

While this "flexible employment" brings many tangible and intangible benefits to workers, on-demand platforms have been facing challenges in matching customers with independent workers due to the uncertainty nature in both worker availability and customer demand. Unlike a traditional firm that can centrally manage its capacity and schedule workers to shift, workers on a platform are independent and self-scheduled, making it harder for platforms to control the number of workers needed at the time and the locations in which they want workers to provide service. Therefore, effectively matching supply with demand is an important objective for the on-demand platforms, since it not only increases a worker's welfare and the platform's revenue but also benefits the entire society by satisfying more customer requirements.

To match worker supply with customer demand, platforms often offer extra compensation in supply-shortage areas to attract more workers. For example, on-demand ride-hailing platforms, such as Uber and Lyft, use dynamic wage and price policy under which drivers receive an additional revenue by serving passengers in high-demand zones. Meanwhile, Didi, China's version of Uber, provides drivers with subsidies if they serve customers in another location as directed by the platform. Many of these policies and their underlying algorithms are designed under the assumption that workers are rational agents who are able to utilize any information provided to them and search for the optimal decisions. However, humans are seldom rational; their decisions and behaviors are often subject to cognitive limitations and biases. If a technology is developed without taking into account these cognitive biases, its benefit to workers, customers and the platform can be limited, or even worse, it may lead to negative outcomes. For example, surge pricing policy adopted by on-demand ride-hailing platforms induces frustrations to the drivers and results in distrust between drivers and the platform. Many drivers have shared their negative experiences in the online discussion forums stating that they regretted chasing the "surge" map because often times they could not get any passenger request after waiting in the surge zone for a long time. This kind of frustration may cause drivers to regret going to the surge zone in the first place, and therefore ignore any market incentives, which is the opposite of the initial objective of the surge price. Such evidence, along with many others, suggests that technologies developed to enhance worker performance must consider worker's behavior in order for them to be effective.

Another important way for a platform to influence worker's decision is to communicate with workers by sharing demand information or providing guidance in the on-demand app. Credible information or reliable suggestions are critical for the system when workers repeatedly interact with the platform. However, compared to the traditional market where demand is the only main source of uncertainty, platforms must also be able to predict worker's behavior, hence the supply, so that customer demand can be better matched with workers on the platform. As a result, a good communication mechanism could be effective to manage worker's relocation decision for on-demand platforms.

The goal of this paper is to determine what behavioral factors may influence workers' relocation decisions, how information about market demand should be communicated to workers to achieve a high efficiency of matching supply with demand, and how an on-demand platform should design financial incentives to induce an adequate amount of workers to relocate to supply-shortage zones once these behavioral factors are incorporated. To answer these questions, we consider an on-demand platform with two adjacent zones, one with more supply than demand (i.e., a supply-overage zone) and the other with more demand than supply (i.e., a supply-shortage zone). Workers, initially located in the supply-overage zone, must decide whether they want to relocate and provide service in the supply-shortage zone but incur a relocation cost. We evaluate workers' equilibrium behavior through analytical modeling, and then test model predictions and establish casual relationships using a series of large-scale controlled lab experiments. Lab experiment allows us to manipulate one variable at a time while controlling for other confounding factors across treatments so that causal effect can be established. Because of its distinctive advantages, lab experiment has been widely adopted in Operations Management field (Donohue et al. 2018), and has been used to discover behavioral biases in many contexts, such as the newsvendor problem (Schweitzer and Cachon 2000; Bolton and Katok 2008), supply chain contracting (Katok and Wu 2008; Becker-Peth et al. 2013; Zhang et al. 2016), revenue management (Bearden et al. 2008; Mak et al. 2014), capacity management (Chen et al. 2012; Cui and Zhang 2018), among many others.

One behavioral factor that may influence workers' relocation decision is "regret aversion". Prior research has shown that decision makers often compare obtained decision outcomes with forgone decision outcomes, and experience a negative feeling of regret if the unchosen action would result in a better payoff (Zeelenberg et al. 1996; Zeelenberg and Beattie 1997). For example, a worker would likely regret not going to a high-demand zone if s/he had not received any customer requests in the current location. Similarly, a worker may also regret for moving to a different location where s/he had failed to fulfill any service requests. As a result, a worker would anticipate this regretful emotion and make decisions to minimize it *ex ante*. We study the influence of regret on workers' relocation decisions in Section

3. Specifically, we incorporate workers' regret aversion behavior into an analytical model and predict that workers are more willing to relocate to the supply-shortage zone compared with the case of no regret. Experimental results confirm our theoretical prediction and find that regret aversion is indeed the underlying behavioral factor that drives the observed overflow of workers to the supply-shortage zone.

After establishing the role of regret aversion, in Section 4, we study two mechanisms the platform may adopt to communicate customer demand to the workers - information sharing and suggestion provision. We focus our investigation on settings where the communication from the platform to its workers is truthful. In other words, the information shared or the suggestion provided by the platform reflects the true demand state in the system, and the workers are informed that these communications are truthful and can be trusted. Controlling the demand communication in this way allows us to examine workers' actions without introducing additional complexities related to how workers would or should trust these communications when the underlying mechanism is unspecified. Our experimental results show that sharing demand information is a better means of communicating customer demand than providing suggested actions, contrary to the analytical model prediction. We further find that workers often ignore these suggestions by failing to perform a Bayesian demand update due to their cognitive limitations. As a result, workers are unable to take advantage of the information behind suggested actions, making suggestion provision a less effective communication mechanism. In fact, according to our experiment, as high as 94% of the platform workers can be matched to a customer demand under the information sharing policy when relocation cost is low. However, when relocation cost is high (such as during rush hours, traffic jams, long distance, etc.), despite being the best policy, sharing demand information can no longer achieve a desirable matching efficiency.

To deal with workers' unwillingness to relocate due to high relocation cost, we examine, in Section 5, how the platform could offer extra financial incentive, referred to as "bonus", to compensate workers for their relocation cost and to induce more workers to move to the supply-shortage zone. Specifically, we study the platform's profit-maximizing bonus level when its workers are regret averse. We focus our investigation on the setting where demand information is directly shared with workers, since we have established that information sharing is a more effective mechanism of communicating customer demand. Our analytical analysis combined with lab experiments indicates that, under certain conditions, workers' behavioral tendency of regret aversion can simultaneously improve the platform's profit, worker surplus and the system matching efficiency. These results illustrate that workers' irrational behavior such as regret aversion can actually benefit the on-demand sharing business.

To the best of our knowledge, we are the first paper to investigate independent worker's behavioral biases in the context of on-demand service platforms. Our research demonstrates that platform workers are irrational agents and their decisions are largely affected by behavioral biases. Consequently, platforms must take these human factors into consideration and design effective policies to increase platform revenue and at the same time benefit the entire society.

2 Literature Review

The emergence and popularity of sharing economy in recent years have raised many interesting research questions and attracted significant academic interest. One of the most distinctive features of an on-demand service platform that differs from a traditional business is that workers serving on the platform are not hired by the platform but independently make their own decisions on when, where and how long to work. In economics, there are a stream of empirical papers studying the elasticity of labor supply when workers have discretion over how much they work (e.g. Chen and Sheldon, 2015; Hall and Krueger, 2016; Hall et al., 2017b; Chen et al., 2017; Angrist and Caldwell, 2017). From the operations perspective, a handful of papers have started to examine the impact of self-scheduling workers on system performance. For example, Ibrahim and Arifoglu (2015) study a setting in which the company decides on the number of workers to employ but workers have the flexibility to choose between work shifts. They show that providing workers with this discretion affects the optimal number of workers to hire. Gurvich et al. (2016) and Taylor (2016) show that, compared to a traditional employer, on-demand platforms may have disadvantages in managing their system due to the decentralization with independent, self-scheduled workers. On the other hand, Benjaafar et al. (2017) show that a platform has the advantage of attracting workers with various availabilities, and hence could benefit from a larger labor supply pool when customers are sensitive to delays. Different from the above mentioned work, we investigate the behavioral aspect of workers in the on-demand platform who have the flexibility to decide the location to serve customers.

While workers may benefit from the flexibility of working for an on-demand platform, it also brings significant operational challenges of managing the service capacity of an on-demand platform with independent worker across different market zones. To address the challenge, a number of papers investigate the role of dynamic wage and price in matching supply with demand when market demand fluctuates. Sheldon (2016), using data from Uber, finds that drivers tend to work longer when earnings are higher (e.g., during price surges). In addition, from a modeling perspective, a few papers (e.g. Cachon et al. 2017, Castillo et al. 2017, Riquelme et al. 2015, Tang et al. 2017, Taylor 2017, Bimpikis 2016, Chen and Hu 2017, Hu and Chen 2017, and Hu and Zhou 2016) investigate the positive impact of dynamic wage/price in a two-sided market. Most of studies, however, are based on a single location. There are a few recent papers that consider the role of surge price in managing workers' availability across locations.

Guda and Subramanian (2017) show that surge price could serve as a credible signal for high demand, which can effectively redistribute drivers to high demand regions. An empirical study by Chen and Sheldon (2015) finds that surge price may result in driver idleness and cause drivers to leave the surge zone. In these studies, drivers are assumed to be rational agents who are able to search for the optimal decisions. Instead, our paper investigates worker's irrational behavior and how their behavioral biases may influence workers' relocation decisions, the platform's policies, and ultimately the performance of on-demand systems.

Finally, a few papers have investigated matching policies without financial incentives. Hu and Zhou (2017) examine the optimal matching policy for a centralized firm in a general setting. Feng et al. (2017) investigate the matching inefficiency of an on-demand ride hailing system when demand and supply are evenly distributed in the system. Ozkan and Ward (2017) propose a CLP-Based matching policy that improves the closest driver (CD) policy when arrival rates are heterogeneous in different regions. Afèche el al. (2018) study the case that self-interested drivers strategically make reposition decisions when demand arrivals are imbalanced in a two-location network. Our research complements these studies by investigating the impact of communication mechanisms with and without compensation on system's efficiency of matching demand with supply.

Human cognitive/behavioral limitations play an important role in decision making. In our problem context, we consider two behavioral biases: regret aversion and ignorance of suggestion due to non-Bayesian information update. In the field of operations management, a number of studies have found empirical evidence that the regretful emotion can change people's decisions *ex ante* (e.g., Simonson 1992, Inman and Zeelenberg 2002). A few recent studies have also used analytical approach and investigated the impact of regret aversion in operations contexts, such as auction (Engelbrecht-Wiggans and Katok 2007), newsvendor problem (Perakis and Roels 2008), dynamic purchase (Diecidue et al. 2012), advance selling (Nasiry and Popescu 2012), and markdown management (Özer and Zheng 2016). A number of studies have shown that human decision makers tend to ignore the information communicated to them because of their lack of trust (Berg et al. 1995). A few studies have examined the role of trust (and trustworthiness) in operations contexts such as forecast information sharing (Özer et al. 2011; 2014). More recently, Özer et al. (2018) demonstrates that trust causes decision makers to ignore suggested actions to a larger degree than they do shared information. Our research shows that workers' ignorance of suggested actions persists even when (dis)trust is fully controlled. In other words, human workers continue to ignore platform's suggestions even if they know that these suggestions are truthful and can be trusted. Workers' ignorance of suggestion is instead caused by their inability to utilize such information to perform demand update. Thus, our research complements the work of Özer et al. (2018) by proposing a new behavioral explanation for why sharing information is a better mechanism than providing suggestions.

3 Worker's Relocation Behavior under Regret

3.1 Theory

We consider a single period setting in which an on-demand platform intends to match independent workers (i.e., supply) and customers (i.e., demand) in two adjacent market zones: Zone A and Zone B. Customers request service through the on-demand platform, and can only be matched with workers in the same zone. Let S_i^0 denote the initial supply in Zone i where $i \in \{A, B\}$, and D_i denote the realized customer demand. We assume $S_A^0 + S_B^0 = D_A + D_B$ and w.l.o.g. $S_A^0 > D_A$ (excess supply in Zone A). That is, there are just enough workers in the platform to fulfill all service requests at the aggregate level, but supply-demand mismatch may exist in each individual zone. For the convenience of the analysis and the experimental implementation, we assume that all workers are initially located in Zone A, i.e., $S_B^0 = 0$[1], and the number of available workers is $S_A^0 = n$.

Let ρ be the initial demand to supply ratio in Zone A. That is, the total number of service requests in Zone A is $D_A = \rho n$, and the total number of service requests in Zone B is then $D_B = (1 - \rho)n$. We assume that ρ follows a uniform distribution on $[0, 1]$. This assumption has two implications. First, the *ex ante* customer demand is evenly distributed in the two zones (i.e., expected demand is $\frac{1}{2}n$ in both zones). Second, the customer demands in the two zones are negatively correlated. For example, the number of customer request on a ride-hailing platform such as Uber is likely to be higher in suburban areas than in the city during the morning rush hour, but the reverse might happen during the evening rush hour (Afèche et al. 2018). The true value of ρ is known by the platform but is not necessarily observed by the workers. At the beginning of the period, workers will decide whether to stay in Zone A or relocate to Zone B at a certain cost. Let $\gamma \in [0, 1]$ represents the proportion of workers who decide to relocate. Then the final number of available workers in Zones A and B are $S_A = (1-\gamma)n$ and $S_B = \gamma n$, respectively. Workers incur a relocation cost c if moving to Zone B, and receive a payoff (i.e., wage) of w for serving a customer in each zone. To avoid trivial cases, we assume that the relocation cost is strictly positive and smaller than the worker's payoff, i.e., $0 < c < w$.

The sequence of events is as follows. Before the start of the period, nature decides the value of ρ, i.e., the demand in both zones. Next, workers simultaneously decide whether to stay in Zone A or move to Zone B. Workers know the distribution of ρ but not the realization, unless the platform communicates this information to them. After the relocation is complete, the platform matches customers with workers in each zone. If the number of available workers is more than the number of customer requests in a

[1] The main insights of our model do not change if we assume $S_B^0 > 0$.

particular zone, the platform randomly chooses a subset of workers to match with customers. On the other hand, if there are fewer workers than customer requests, all the workers in that zone are assigned to customers. Unfulfilled customer requests are completely lost. We assume that all customer requests take up the entire period to complete, and hence a worker cannot be matched with more than one customer. At the end of the period, workers who were assigned with customers complete their service and all customers leave the platform.

In the baseline model, as a benchmark, we consider the case that the platform neither offers any financial compensation nor communicates realized demand to the workers. The probability with which a worker in zone i receives a service request, after their relocation decision, is $\min(1, \frac{D_i}{S_i})$, for $i \in \{A, B\}$. A worker would receive an expected payoff of $\pi_A = w \min(1, \frac{D_A}{S_A}) = w \min(1, \frac{\rho}{1-\gamma})$ if staying at Zone A, and $\pi_B = w \min(1, \frac{D_B}{S_B}) - c = w \min(1, \frac{1-\rho}{\gamma}) - c$ if relocating to Zone B.

We capture the "aversion to regret" (Zeelenberg et al. 2000) that affects workers' relocation decisions in the following way. Regret stems from decision makers' counterfactual thinking, i.e., the "might-have-been" reconstructions of past outcomes (Roese 1994). Due to the counterfactual thinking, decision makers often compare the outcome of the chosen action with the forgone outcome of an unchosen one, and experience a negative feeling of regret if the chosen action resulted in an undesired outcome. In our setting, a worker may experience a regret emotion if s/he fails to obtain a demand in the chosen zone, while s/he would have received a demand and earned a positive payoff had s/he chosen the other zone[2].

To formally model the negative emotion due to regret, we follow the approach developed by Bell (1982), Loomes and Sugden (1982), and more recently Özer and Zheng (2016), in which regret aversion is modeled as the counterfactual payoff multiplied by the probability with which this particular regret occurs. We then characterize the utility that a worker will receive when choosing Zone $i \in \{A, B\}$ as

$$u_i(\eta) = \pi_i - \eta \cdot \pi_{-i} \cdot \left(1 - \min(1, \frac{D_i}{S_i})\right). \tag{1}$$

The first term π_i is a worker's expected payoff received in Zone i. The second term captures the disutility due to the negative feeling of regret. The value $1 - \min(1, \frac{D_i}{S_i})$ represents the probability with which a worker fails to serve a customer and thus experiences regret. The parameter $\eta \geq 0$ measures the degree of a worker's aversion to regret, which is the ratio of the marginal value of regret to the actual monetary value. When $\eta = 0$, workers become rational decision makers who do not exhibit any regretful feelings. In this case, our model reduces to a standard rational model in which decision makers care solely about their monetary payoffs. We do not impose an upper bound for the regret aversion parameter η, but in

[2] A worker not receiving a demand suggests that there are more workers than customers in this zone. Since the total supply and demand across zones are equal, there must be a supply shortage in the unchosen zone. Therefore, this worker would guarantee a demand had s/he chosen the other zone.

practice, η is likely to be between 0 and 1 since one unit of actual monetary payoff is likely to be valued more than one unit of counterfactual payoff (Özer and Zheng 2016).

We next characterize the equilibrium for the workers' relocation decision, revealed by $\gamma(\eta)$, which represents the percentage of workers relocating to Zone B and is a function of η. If workers always receive a higher utility in Zone A than in Zone B, the equilibrium $\gamma^*(\eta)$ should be 0; that is, all workers choose to stay. To the contrary, all workers will choose to move (i.e., $\gamma^*(\eta) = 1$) if their utility in Zone B is always higher. When $\gamma(\eta) \in (0, 1)$, a proportion of workers choose to relocate to Zone B, and an equilibrium $\gamma^*(\eta)$ should be the point where a worker would expect to have the same *ex ante* utility regardless which zone s/he chooses (i.e., s/he is indifferent between staying in Zone A or moving to Zone B). Hence, an equilibrium $\gamma^*(\eta) \in (0, 1)$ must satisfy $Eu_A(\eta) = Eu_B(\eta)$.

To evaluate the overall system performance under equilibrium, we define the supply-demand *matching efficiency* $M(\eta)$, the percentage of workers who have fulfilled a customer request (or the percentage of customers whose request is fulfilled on the platform), as:

$$\begin{aligned} M(\eta) &= \frac{\min(S_A, D_A) + \min(S_B, D_B)}{n} \\ &= \min(1 - \gamma^*(\eta), \rho) + \min(\gamma^*(\eta), 1 - \rho). \end{aligned}$$

The relocation equilibrium $\gamma^*(\eta)$ and the resulting matching efficiency $M(\eta)$ is summarized in the following theorem.

Theorem 1. *(a) When* $c \geq \frac{1+\eta}{2+\eta}w$, $\gamma^*(\eta) = 0$*; When* $0 < c < \frac{1+\eta}{2+\eta}w$, $\gamma^*(\eta) = \frac{1}{2} - \frac{4c+\eta c}{4w+2\eta(2w-c)} > 0$*. (b) The matching efficiency is* $M(\eta) = \frac{1}{2} + \gamma^*(\eta) - (\gamma^*(\eta))^2$*. (c) Both* $\gamma^*(\eta)$ *and* $M(\eta)$ *are weakly increasing in* η*.*

All proofs are included in the Online Supplement. Theorem 1 indicates that the presence of regret ($\eta > 0$) encourages more workers to relocate to Zone B. In the case of no regret, the equilibrium $\gamma^*(0) = \max(0, \frac{1}{2} - \frac{c}{w})$ is always less than $\frac{1}{2}$. In other words, there are always more workers choosing to stay in Zone A than moving to Zone B. As a result, workers in Zone A are more likely to experience regret because there is a higher chance of not getting a customer demand due to excessive supply in Zone A. This feeling of regret leads to additional workers moving to Zone B, the supply-shortage zone, and thus an increased supply-demand matching efficiency.

3.2 Experimental Validation

Our analytical analysis indicates that the behavior of regret aversion increases the number of workers relocating to Zone B, compared to the case of no regret. To test this notion, and to verify that regret aversion is in fact the driving factor, we conduct a controlled lab experiment consisting of three treatments with human decision makers (one baseline group and two validation groups). We consider both low and high relocation cost using a within-subject design. In other words, the relocation cost may change from round to round and the sequence is determined randomly. This design is consistent with the real-world situation in which a worker (e.g., a Uber driver) may experience different costs in different time of the day (e.g., rush vs. non-rush hours). We set the worker's wage $w = 10$ and relocation cost $c = 2$ (low cost) or 8 (high cost).

The experiment was conducted in a computer laboratory at the business school of a large research university. We recruited $n = 150$ undergraduate students as participants (50 in each treatment), all of whom were sophomores or juniors from a variety of majors in the business school. This large number of participants ensures that each individual's decision will have little impact on the outcome of the entire group. Once entering the computer laboratory, participants were randomly seated in front of a computer terminal. The researchers then read aloud the instructions (detailed instructions are provided in the Online Supplement). We told the participants that all 50 of them were service providers who were initially located in Zone A, and asked them to decide simultaneously whether they wanted to stay in Zone A or move to Zone B at a certain cost. We emphasized that the customer demand in Zone A, D_A, was less than 50 and could be any whole number from 0 to 49 with equal probability, and that the demand in Zone B was $50 - D_A$. We asked participants to make the stay-or-move decision for 40 rounds and emphasized that both the relocation cost and customer demand could change from round to round. We pre-generated 20 demand draws for each of the two cost scenarios (i.e., $c = 2$ and $c = 8$), resulting in a total of 40 cost/demand pairs. The participants were not informed about the demand realization (but only the distribution) before, during or after each round.

During the illustration, participants were allowed to ask any questions. After all questions were answered, we gave participants two exercises to ensure their understanding of the problem scenario. Next, participants made their decisions on a computer programed using zTree (Fischbacher 2007). In each decision round, participants chose one of the two options – staying in Zone A or moving to Zone B after observing the relocation cost for that round. After all participants finished their decisions, they advanced to a second screen, which displayed their decision, whether they received a customer demand, and their earnings for that round. After completing the experiment, participants were paid in cash, which was converted from their total earnings over all 40 decision rounds. The experiment lasted about 60 minutes, with an average payment of about RMB 30, which is equivalent to US \$8.81 after adjusting by purchasing power parity.

We refer to this basic treatment as the *baseline* treatment. Table 1 summarizes the observed percentage of relocation to Zone B and the resulting matching efficiency in the *baseline* treatment. Compared with the theoretical prediction without regret ($\eta = 0$), we find that the observed percentage of move-

Table 1: Model Predictions and Experimental Results for the Baseline Treatment.

	Relocation Percentage (γ^*)		Matching Efficiency (M)	
	Theory ($\eta = 0$)	Obs.	Theory ($\eta = 0$)	Obs.
Low cost (c=2)	0.3	0.382***	0.71	0.750
High cost (c=8)	0	0.222***	0.5	0.708**

Note: ***p<0.001; **p<0.01; *p<0.05.

ment is significantly higher in both cost conditions[3]. In other words, participants in our experiment chose to move to Zone B more frequently, an outcome consistent with the behavior of regret aversion. Furthermore, this additional flow of workers to the supply-shortage zone leads to an increased performance for the system. Although the increase in matching efficiency is statistically significant only when cost is high, the presence of regret indeed results in a higher percentage of fulfilled customer demand compared to the case of no regret.

One might argue that this observed overflow of workers to the supply-shortage Zone B might be due to factors other than regret. For example, since *ex ante* customer demand is evenly distributed between the two zones, workers are more likely to obtain a demand in Zone B (and thus receive a positive earning) than in Zone A. If workers are risk averse - i.e., if they prefer a safer option to a riskier one, we might also observe a higher percentage of workers relocating to Zone B (a "safer" zone) than predicted by rational expected utility theory. In other words, the less risky choice Zone B is also the regret-minimizing option. To rule out this possible explanation and to demonstrate that regret aversion is in fact the underlying mechanism that drives worker's behavior, we conducted two validation treatments by manipulating the salience of regret. In the first treatment, we modify the demand distribution so that the feeling of regret becomes less salient, while in the second treatment, we provide feedback information to emphasize counterfactual payoffs.

The feeling of regret arises when decision makers compare obtained decision outcomes with forgone decision outcomes. An important assumption in regret theory is that the outcomes of both the chosen and unchosen option must be revealed to the decision maker. In his seminal work, Zeelenberg (1999) argues that "[i]f there is no explicit feedback on forgone outcomes, a decision maker cannot compare *what is* with *what would have been* ... [and hence] there is no need to anticipate future regret" (p. 96-97). Applying this principle, in the first validation treatment, we make the forgone profit less salient by equalizing the customer demand in both zones; that is, the new customer demand in Zone B becomes $D'_B = D_A = \rho n$ (as opposed to $1 - \rho$), with parameter ρ uniformly distributed in $[0, 1]$. We refer to this

[3]Unless noted otherwise, we use Wilcoxon test to examine the differences. We also performed an individual level analysis using random-effect logistics regression (since the response variable is binary). The results are largely consistent with the Wilcoxon test.

treatment as *demand* treatment.

The *demand* treatment serves two purposes. First, the worker's regretful feeling is made less salient. Compared to the *baseline* treatment with $D_A = \rho n$ and $D_B = (1-\rho)n$ in which a worker who did not receive a demand would know with certainty the foregone decision outcome, in the *demand* treatment the foregone outcome is not obvious to the workers. For example, if the demand in both zones turns out to be low, a worker who did not receive a customer in Zone A does not know whether s/he would have received a customer in Zone B, and hence cannot compare "what is" with "what might have been". As a result, the regretful feeling due to not choosing the alternative option becomes less strong. Therefore, we expect a lower percentage of movement to Zone B in the *demand* treatment compared to the *baseline* case.

The second purpose of the *demand* treatment is to rule out the possible alternative explanation of risk aversion. Changing the demand in Zone B from $(1-\rho)n$ to ρn does not alter the probability of obtaining a customer demand and thus the probability distribution of worker's payoff. In fact, it is easy to verify that the equilibrium relocation percentage $\gamma^*(0)$ in the *demand* treatment is identical to that in the *baseline* treatment. Therefore, the theory of risk aversion should predict no significant difference in workers' relocation outcome in these two treatments.

In the second validation treatment, referred to as the *feedback* treatment, we make forgone profit more salient by provide explicit feedback (the demand condition is kept the same as the *baseline* treatment). Specifically, we inform participants at the end of each decision round about the payoff they would have received had they chosen the other zone[4]. Prior research has found empirical evidence that providing feedback on counterfactual outcome induces regret-averse behavior among decision makers (e.g., Humphrey 2004; Engelbrecht-Wiggans and Katok 2009). This implies that if regret aversion is indeed the driving behavioral factor in our problem setting (i.e., workers have already undergone counterfactual thinking), whether forgone profit is emphasized or not should not alter the workers' behavior. Thus, we expect no difference should exist between the *feedback* and the *baseline* treatments.

Table 2 reports the experimental results of the two validation treatments, which coincide with our expectation. We find a significant lower portion of workers moving to Zone B in the *demand* treatment but no statistical difference in the *feedback* treatment, compared with the *baseline*. Together these results indicate that regret aversion is in fact the underlying mechanism that drives a worker's relocation decision.

[4]In the experiment, at the end of each decision round, a message was displayed on the screen below the earned profit stating the profit they would have earned in other zone.

Table 2: Relocation Rate under the Demand and Feedback Treatments

	Baseline	*Demand*	*Feedback*
Low cost (c=2)	0.382	0.333**	0.386
High cost (c=8)	0.222	0.103***	0.199

Note: ***$p<0.001$; **$p<0.01$; *$p<0.05$.

3.3 Summary

Thus far we have demonstrated that the behavioral tendency of regret aversion leads more workers to the supply-shortage zone. However, this additional flow of workers still fails to translate to a desirable matching of supply with demand. According to our experiment (Table 1), the matching efficiency is only 75.0% under low relocation cost and 70.8% under high cost, leaving almost 30% of workers and 30% of customers unmatched. This low matching efficiency may in turn lead to lost profits for the platform and inefficiency in matching supply with demand.

The demand-supply mismatch can be attributed to two major factors: uncertainty in customer demand and high relocation cost. Because workers only know the demand distribution not the realization, the best scenario for the system is to have equal number of workers in both zones. However, according to Theorem 1, in equilibrium, the portion of workers who choose to relocate to Zone B is always less than half. Even worse, when relocation cost is very high (e.g., rush hours, heavy traffic, long distance etc.), all workers would rather stay in Zone A and take the risk of not getting a customer request, than relocating to Zone B where a demand is guaranteed. Therefore, to reduce the demand-supply mismatch in both zones, the platform must financially *compensate* workers for their relocation cost, and/or effectively *communicate* demand information to workers so that they have a better knowledge about the realization (as opposed to the distribution) of customer demand. A preliminary experimental study (reported in the Online Supplement) shows that offering worker compensation alone fails to increase the platform's matching efficiency. Therefore, to further improve the system performance, the platform should first design an effective mechanism to communicate demand information to their workers before implementing any compensation policy. We investigates two communication mechanisms in the next section.

4 Platform's Mechanism to Communicate Demand

We consider two mechanisms that a platform may adopt to communicate customer demand to workers.

1. *Information Sharing (Info)*: The platform shares with all workers the demand information, i.e., the value of ρ.

2. *Suggestion Provision (Sugg)*: Based on the demand information ρ, the platform randomly selects $(1-\rho)n$ number of workers and suggests them moving to Zone B, and the rest staying in Zone A.

4.1 Theory

One way to communicate demand information to workers is simply share the demand information ρ (*Info* policy). In this case, workers will make the stay-or-move decision after being informed about the demand ρ. When the demand in Zone B is high (low), it is expected that more (fewer) workers will choose to relocate. Thus, the equilibrium γ becomes a function of ρ. Given a value ρ, workers will evaluate their utility in each location, and the equilibrium is reached at the point that satisfies $u_A(\eta|\rho) = u_B(\eta|\rho)$ with a worker's utilities in Zone A and Zone B defined in Equation (1). The following Theorem summarizes the equilibrium behavior $\gamma_I^*(\eta|\rho)$ and resulting matching efficiency $M_I(\eta)$ under the *Info* policy.

Theorem 2. *When workers are informed about customer demand ρ, (a) if $c \geq \frac{(1+\eta)(1-\rho)}{1+\eta(1-\rho)}w$, $\gamma_I^*(\eta|\rho) = 0$; if $c < \frac{(1+\eta)(1-\rho)}{1+\eta(1-\rho)}w$, $\gamma_I^*(\eta|\rho) = 1 - \frac{w+\eta(w-c)}{(1+\eta)(w-c)}\rho > 0$. (b) The matching efficiency at ρ is $M_I(\eta|\rho) = \rho + \gamma_I^*(\eta|\rho)$. (c) In the long run, $\gamma_I^*(\eta) = E_\rho[\gamma_I^*(\eta|\rho)] = \frac{1}{2} - \frac{1}{2}\frac{c}{w+\eta(w-c)}$ and the overall matching efficiency is $M_I(\eta) = E_\rho[M_I(\eta|\rho)] = \frac{1}{2} + \gamma_I^*(\eta)$. (d) Both $\gamma_I^*(\eta)$ and $M_I(\eta)$ are strictly increasing in η.*

Theorem 2 suggests that whether workers would move to Zone B is dependent on the relocation cost. When cost is high ($c \geq \frac{(1+\eta)(1-\rho)}{1+\eta(1-\rho)}w$), no workers choose to relocate because staying in Zone A would always yields a higher utility. As the cost decreases, a worker's expected utility in Zone B increases, and thus s/he starts to move to the supply-shortage zone. Moreover, since demand information is revealed to the workers, the relocation equilibrium is now a function of ρ. To make a fair comparison, we calculate the long-run expected relocation percentage and matching efficiency (after taking account the entire distribution of ρ). It becomes obvious that revealing demand information to workers results in a higher percentage of movement to the supply-shortage Zone B (i.e., a higher γ_I^*), and hence achieves a greater efficiency in matching customer requests with workers, compared with the case in which demand information is not revealed (Theorem 1). Finally, consistent with the prior results in Section 3, the presence of regret aversion causes additional flow of workers to the supply-shortage zone and thus resulting in a higher system efficiency.

One potential disadvantage of the *Info* policy might be that the platform has little control over who and how many workers will eventually move to the supply-shortage zone, because workers are still self-scheduling - they make stay-or-move decisions on their own. To better coordinate the workers' action, the platform may instead provide a concrete suggestion as to which zone the workers should provide their service at (*Sugg* policy). Different from the *Info* policy, the *Sugg* policy allows the platform to target at a specific population of workers, and by influencing their actions the platform might achieve a better outcome. Note that, since workers on the platform are independent service providers rather than employees, the platform is unable to force any actions on them. Hence, workers are free to decide whether they want to follow or disregard the platform's suggestion.

To formally model the *Sugg* policy, we posit that, after demand ρ is realized, the platform randomly selects $(1-\rho)n$ number of workers and suggests them moving to Zone B, while the rest ρn workers staying in Zone A (their initial zone). Based on the suggestion given to them, workers would then have an updated belief about the true demand distribution. Let X be an indicator variable representing the suggestion a worker receives from the platform, and

$$X = \begin{cases} 1 & \text{if the suggestion is to move to Zone } B \text{ ;} \\ 0 & \text{if the suggestion is to stay in Zone } A. \end{cases} \tag{2}$$

If the suggestion is to relocate ($X = 1$), a worker's updated demand density function according to the Bayesian rule, becomes:

$$f_S(\rho|X=1) = \frac{P(X=1|\rho)\cdot f(\rho)}{P(X=1)} = \frac{1-\rho}{\int_0^1 (1-\rho)d\rho} = 2(1-\rho). \tag{3}$$

On the other hand, if the suggestion is to stay in his or her initial zone ($X = 0$), the updated demand density function becomes:

$$f_S(\rho|X=0) = \frac{P(X=0|\rho)\cdot f(\rho)}{P(X=0)} = \frac{\rho}{\int_0^1 \rho d\rho} = 2\rho. \tag{4}$$

According to the Bayesian update process, workers should no longer believe the customer demand to be uniformly distributed between the two zones. Rather, a worker, who was told to move to Zone B, would think it is more likely to observe a higher demand in Zone B than in Zone A, as suggested by the updated demand function in Equation (3) and thus is more willing to follow the platform's suggestion. Similarly, if a worker is told to stay in Zone A, s/he is more likely to do so because s/he now believes the demand in Zone A to be high, as shown by Equation (4). Therefore, the underlying mechanism of suggestion is to alter a worker's belief about the final demand distributed in each zone.

To formally analyze the equilibrium outcome, we again compare workers' utility in each zone. Since the suggestions received by workers may differ ($X = 1$ or $X = 0$), we first consider the relocation decision for each group.

Lemma 1. *(i) Workers who are told to stay in Zone A will always stay. (ii) For workers who are told to move to Zone B, the percentage of movement is defined by $\alpha^*(\eta)$. Furthermore, if $c \geq \frac{2+2\eta}{3+2\eta}w$, $\alpha^*(\eta) = 0$; if $c < \frac{2+2\eta}{3+2\eta}w$, $0 < \alpha^*(\eta) < 1$, and $\alpha^*(\eta)$ can be obtained by solving $\frac{(2-\alpha)\alpha+2(1-\alpha)\log(1-\alpha)}{\alpha^3} = \frac{(1+\eta)(w-c)}{w+\eta(w-c)}$.*

Lemma 1 shows that platform workers should remain in their initial location if they are told to do so. If they are told to leave their initial zone, they should not always follow this suggestion ($\alpha^*(\eta) < 1$). This illustrates that, since it is workers, not the platform, who bear the relocation cost, misalignment exists between a worker's incentive to relocate and the platform's goal of improving the system efficiency. This is particularly true if the relocation cost is sufficiently high (i.e., $c \geq \frac{2+2\eta}{3+2\eta}w$), in which case workers would always prefer to stay in Zone A, even if the platform suggests they leave.

After characterizing how workers' decisions are influenced by a suggested action, we are able to evaluate the relocation equilibrium, which follows directly from Lemma 1.

Theorem 3. *When workers are provided with a suggested action, (a) the equilibrium is* $\gamma_S^*(\eta|\rho) = \alpha^*(\eta) \cdot (1-\rho)$. *(b) The matching efficiency at* ρ *is* $M_S(\eta|\rho) = \rho + \gamma_S^*(\eta|\rho)$. *(c) In the long run,* $\gamma_S^*(\eta) = E_\rho[\gamma_S^*(\eta|\rho)] = \frac{1}{2}\alpha^*(\eta)$ *and the overall matching efficiency is* $M_S(\eta) = E_\rho[M_S(\eta|\rho)] = \frac{1}{2} + \gamma_S^*(\eta)$. *(d) Both* $\gamma_S^*(\eta)$ *and* $M_S(\eta)$ *are weakly increasing in* η.

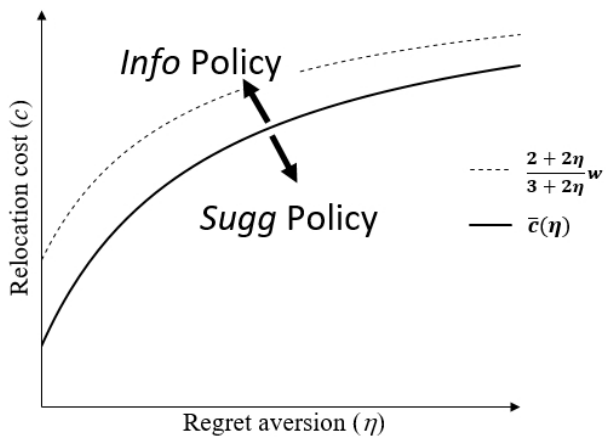
Recall that the platform will inform $(1-\rho)n$ number of workers to move, the exact number of supply needed in Zone B. According to Lemma 1, only a portion $\alpha^*(\eta)$ of them end up moving to Zone B. Thus, the final relocation equilibrium is $\alpha^*(\eta) \cdot (1-\rho)$, which is dependent on the demand ρ. In the long run, after considering the entire distribution of ρ, the equilibrium becomes $\frac{1}{2}\alpha^*(\eta)$.

Now we compare the matching outcome achieved by the platform under the two communication mechanisms. The following proposition summarizes the results.

Proposition 1. *There exists a threshold* $\bar{c}(\eta) \in (0, \frac{2+2\eta}{3+2\eta}w)$, *such that the overall matching efficiency is (i) higher under the Info policy if* $\bar{c}(\eta) < c < w$ *, (ii) higher under the Sugg policy if* $0 < c < \bar{c}(\eta)$, *and (iii) the same for both policies if* $c = \bar{c}(\eta)$. *Furthermore, the threshold* $\bar{c}(\eta)$ *is increasing in* η.

Figure 1 plots how the threshold $\bar{c}(\eta)$ changes with η. First, when the relocation cost is high, i.e., $c \geq \frac{2+2\eta}{3+2\eta}w$ (above the dash line), under the *Sugg* policy, according to Lemma 1, $\alpha^*(\eta) = 0$ implies that no workers would be willing to relocate to the supply-shortage Zone B. To the contrary, the *Info* policy always results in some movements to Zone B (Proposition 2). As a result, the *Sugg* policy performs worse than the *Info* policy. As the relocation cost decreases, the *Sugg* policy starts to take effect ($\alpha^*(\eta) > 0$). When the cost falls below a certain threshold $\bar{c}(\eta)$ (i.e., below the solid line), *Sugg* policy results in a larger number of workers moving to Zone B, leading to a higher matching efficiency for the platform. Finally, $\bar{c}(\eta)$ increases with η, indicating that sharing demand information is a better way of communicating demand only when workers' relocation cost is high and when workers are not quite averse to regret.

Figure 1: Matching Efficiency Comparison: Info Policy vs. Sugg Policy



4.2 Experimental Validation

The above analysis indicates that providing workers with suggested actions (*Sugg* policy) is a better mechanism to communicate customer demand with workers when relocation cost is low, while sharing demand information (*Info* policy) is more effective when relocation cost is high. We conduct a controlled lab experiment to test this prediction.

We recruited 100 participants from the same subject pool, with $n = 50$ for each policy treatment. The experimental protocol is identical to the *baseline* treatment as described in Section 3.2 with the following exceptions. In the *Info* treatment, the demand information in both zones, D_A and D_B, were displayed on the computer screen in the beginning of each period. In the *Sugg* treatment, the computer randomly selected D_B number of participants and suggested them (by showing a message on the computer screen) moving to Zone B and the rest staying in Zone A. However, we allowed participants to disregard this suggestion and choose the opposite option if they wanted to. Participants were informed that the exact D_B number of participants would be selected to receive a suggestion to relocate. We also emphasized the fact that if everybody followed their own received suggestion, a customer demand would be guaranteed for everyone. By doing so we made sure that our participants knew the demand being communicated to them were truthful and that any observed deviations from theory were not due to workers' lack of trust.

The theoretical predictions with no regret ($\eta = 0$) are summarized in Table 3 under the "Theory" columns. We calculate the theoretical equilibrium for a given demand ρ and for the long run. According to Theorems (2) and (3), we should expect to observe a higher percentage of relocation and matching efficiency due to workers' regret-aversion behavior. Additionally, Proposition 1 suggests that compared with the *Info* policy, we should expect the relocation percentage and the resulting efficiency to be higher

Table 3: Model Predictions and Experimental Results for Info and Sugg Policies.

	Relocation Percentage (γ^*)			Matching Efficiency (M)		
	Theory ($\eta = 0$)			**Theory** ($\eta = 0$)		
	Given ρ	Expected	**Actual**	Given ρ	Expected	**Actual**
Low cost (c=**2**)						
Info	$\max(0, 1 - 1.25\rho)$	0.4	0.446**	$\max(\rho, 1 - 0.25\rho)$	0.9	0.944**
Sugg	$0.94(1 - \rho)$	0.472	0.429	$0.94 + 0.06\rho$	0.972	0.861[a]
High cost (c=**8**)						
Info	$\max(0, 1 - 5\rho)$	0.1	0.261***	$\max(\rho, 1 - 4\rho)$	0.6	0.779***
Sugg	0	0	0.222***	ρ	0.5	0.712***

[a] Actual matching efficiency is significantly below the theoretical value with p<0.001.

Note: ***p<0.001; **p<0.01; *p<0.05.

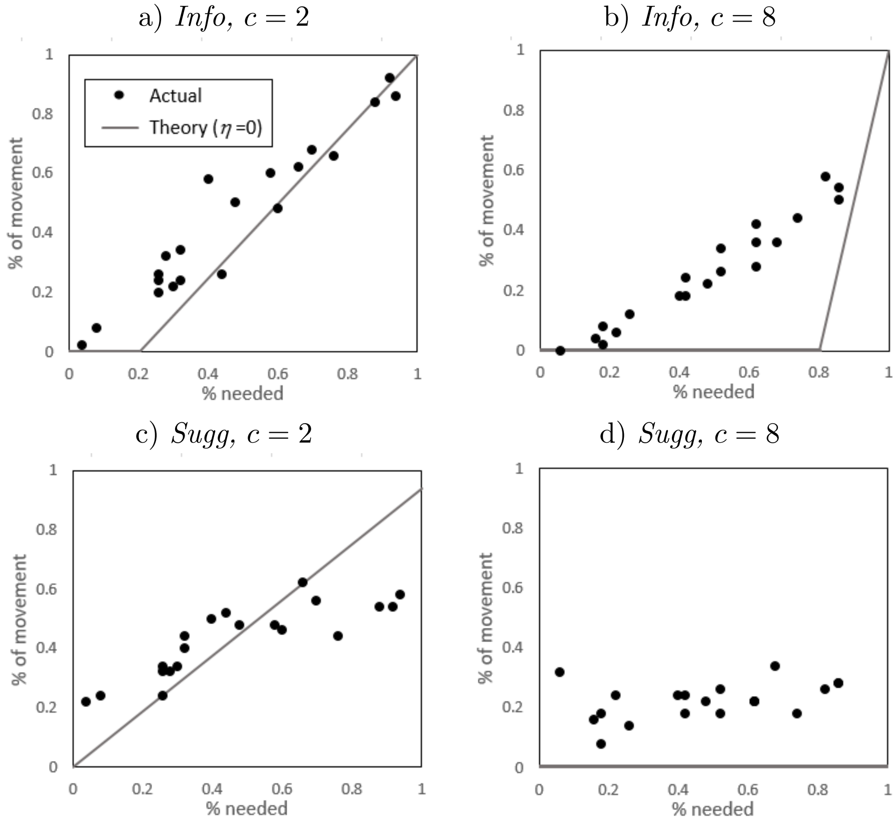
under the *Sugg* policy for low cost, but lower for the high cost. The experimental results are reported in Table 3 under the "Actual" columns.

Figure 2 plots the observed percentage of participants moving to Zone B (y-axis) against the percentage of workers needed in Zone B ($1 - \rho$, x-axis) in each decision round. Since the demand information is communicated to the participants through either information sharing or suggestion, we would expect a strong correlation between the observed moving percentage and the demand in Zone B. We observed this relationship in three of the four cases, except for the *Sugg* treatment with high relocation cost (Figure 2d), in which the observed percentage is positive but not related to the demand.

We first compare the observed moving percentage with theoretical predications. For the *Info* treatment (Figure 2a and 2b), we find that the percentage of relocation is higher than theory in both high and low cost cases ($p = 0.002$ for $c = 2$ and $p = 0.000$ for $c = 8$). This result reinforces our theoretical prediction, indicating that the regret aversion encourages more people to move to Zone B than the case of no regret.

For the *Sugg* treatment, when relocation cost is high (Figure 2d), we also find a higher moving percentage compared with the no-regret case ($p = 0.000$). Recall that standard theory suggests that, when relocation cost is high, workers should disregard any suggestion and behave the same way as if the suggestion were not provided (i.e., the same as the *baseline* case studied in Section 3). Further analysis suggests that the percentage of relocation do not differ significantly from the *baseline* treatment for $c = 8$, as reported in Table 1. However, when relocation cost is low ($c = 2$), we find the average observed percentage is lower than the no-regret case, even though this difference is not statistically significant. This result is rather surprising and does not coincide with our theoretical prediction as suggested in Theorem 3 in that the observed relocation to Zone B should be higher due to the worker's aversion to regret. As shown in Figure 2c, when the demand in Zone B is low, more workers chose to relocate than needed, while when demand in Zone B is high, not enough workers chose to do so.

Figure 2: Observed Percentage of Movement vs. Percentage of Workers Needed in Zone B (Info and Sugg Treatments).



Note. Each dot represents the observed percentage in one decision round.

This implies that a significant portion of workers tend to ignore suggestions while in theory they should not do so. The experimental data shows as much as 36% of the occasions (171 out of 474) in which a participant who was told to move to Zone B ended up staying in Zone A, while standard theory predicts this percentage to be at most 6% (i.e., $1 - \alpha^*(0)$). Similarly, the percentage of participants moving to Zone B when they were told to stay in Zone A was 24% (126 out of 526 occasions), much higher than the theoretical prediction of 0%.

Because of the existence of the workers who ignore suggestions, the *Sugg* policy does not perform as well as what the theory predicts. In fact, when cost is low, we expect the efficiency to be at least as high as 97.2%, but the observed efficiency is only 86.1%, significantly below this benchmark ($p = 0.000$). As a result, the *Info* policy instead yields a higher matching efficiency than the *Sugg* policy (0.944 vs. 0.861, $p = 0.015$), indicating that sharing customer demand information is a more effective communication approach than providing suggested actions, opposite to what theory predicts.

We suspect that the worker's ignorance of suggested actions is caused by their cognitive limitation. Recall that standard theory assumes that workers are fully rational in that they are able update their belief about the demand distribution using the suggestion given by the platform. According to Equations (3) and (4), workers should believe customer demand to be higher in their suggested zone. However, some naive workers may not perform this update due to their limited thinking capability and thus believe the demand distribution continues to be uniformly distributed.

To verify that the worker's ignorance of suggested actions is indeed due to their inability to perform Bayesian update, we conducted two validation treatments with each changing one factor to the basic *Sugg* setting. Both validation treatments followed the same protocol as in the *Sugg* treatment and were conducted with 50 participants in each, who were recruited from the same subject pool. The first treatment is identical to the basic *Sugg* setting except that in each round we asked participants, after receiving their suggestion and before making a decision, which zone (A or B) they believe would have a high customer demand. We emphasized the fact that this question was only to ask about their belief, and their final relocation decision did not have to follow this belief. We gave one extra experimental dollar in each round to those who correctly picked the zone that had a high realized demand[5]. The total cumulative bonuses across all 40 rounds were converted to cash and paid to participants in additional to their game earnings. If all workers perform the Bayesian update as described in Equations (3) and (4), we should observe 100% choosing their suggested zone. By contrast, if none of the workers update their belief, we should see a 50-50 choice split between the two zones. In reality, if there is a mixed of workers, we expect this percentage to be between 50% and 100%. The experimental data shows that 64.65% of the incidents (1293 out of 2000) workers ended up choosing their suggested zones as the high-demand zone, and this percentage is significantly greater than 50% ($p = 0.000$) and smaller than 100% ($p = 0.000$). This result confirms the notion that some but not all workers perform a Bayesian update on the demand distribution[6].

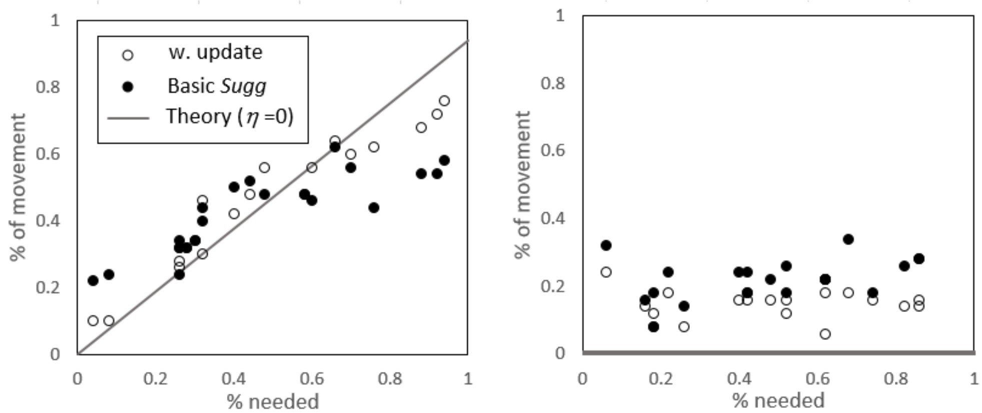
If we explicitly provide the updated demand distribution to the workers, would that change their relocation behavior? We examine this scenario in the second validation treatment. Specifically, after receiving a suggestion, participants were told that the demand is more likely to be high in their suggested zone than that in the un-suggested zone. We illustrated the meaning of "more likely to be high" using a histogram that plots the updated probabilistic distribution of customer demand in each zone (i.e., Equations (3) and (4)). If we perform this demand update for the workers, we would expect a behavior more in line with Theorem 3. Figure 3 plots the percentage of movement when providing the updated demand distribution (circle) compared with the basic *Sugg* setting (dot). We find that when updated demand distribution was explicitly provided to workers, the relocation percentages are much closer to

[5] After all 40 rounds were completed, we told participants how many times they had picked the high-demand zone. We did not reveal this result after each round.

[6] We did not find significant differences in relocation percentage or in matching efficiency between this treatment and the basic *Sugg* treatment. Thus, asking participants about their belief does not influence their behavior.

Figure 3: Moving Percentage When Providing Demand Updates vs. Basic Setting

a) $c = 2$ b) $c = 8$



Note. Each dot/circle represents the observed percentage in one decision round.

the theoretical prediction (solid line) for both cost conditions. As a result, in the low cost condition ($c = 2$), the matching efficiency significantly increased from 0.861 to 0.924 ($p = 0.002$). However, when cost is high ($c = 8$), since fewer workers were willing to relocate to Zone B due to belief update, the matching efficiency significantly decreased from 0.712 to 0.651 ($p = 0.002$). Thus, demand updating based on suggested actions can lead to a worse outcome for the system when worker's relocation is high.

4.3 Summary

Although our analytical model predicts that providing suggested actions to workers regarding where they should provide their service seems to be a better way of communicating customer demand, our experimental results, however, suggest otherwise. This deviation from theory is caused by some workers' ignorance of suggestions due to their inability to update beliefs about demand. As a result, simply sharing demand information with workers and allowing them to decide their own actions seem to be a more effective approach. In fact, when workers' relocation cost is low, sharing demand information can achieve a very high matching efficiency of 94.4%. However, when relocation cost is high, sharing information alone is no longer as effective, with an efficiency of 77.9% according to Table 3. Consequently, in order to incentivize more workers to move to the supply-shortage zone, the platform may need to consider offering additional financial payment to compensate for workers' high relocation cost. We refer to this extra compensation as "bonus". We will study how the platform should decide the optimal level of bonus in Section 5.

5 Platform's Optimal Bonus

5.1 Theory

In this section, we consider a platform offers a bonus, denoted as r, to incentivize workers to relocate to the supply-shortage zone. This bonus is in addition to the base wage w and available only to those who relocate *and* serve a customer. In practice this bonus may take a variety of forms, such as dynamic wage adopted by Uber and subsidy offered by DiDi. We focus on the case where the platform shares demand information with its workers since, as shown in Section 4, information sharing is a more effective way of communicating demand than providing suggested actions. That is, workers make the stay-or-move decision after being informed about the demand state ρ. Following a similar analysis that leads to Theorem 2 in Section 4, we can characterize a worker's relocation equilibrium $\gamma^*(\eta|\rho)$ with bonus r for a given demand ρ as:

$$\gamma^*(\eta|\rho) = \begin{cases} 1 - \frac{w+\eta(w+r-c)}{(1+\eta)(w+r-c)}\rho & \text{if } \rho \in \left[0, \frac{(1+\eta)(w+r-c)}{w+\eta(w+r-c)}\right) \\ 0 & \text{if otherwise} \end{cases}, \text{ when } r \leq c, \text{ and} \tag{5}$$

$$\gamma^*(\eta|\rho) = \begin{cases} \frac{(1+\eta)w+r}{(1+\eta)w+c}(1-\rho) & \text{if } \rho \in \left(\frac{r-c}{(1+\eta)w+r}, 1\right] \\ 1 & \text{if otherwise} \end{cases}, \text{ when } r > c. \tag{6}$$

Workers' relocation decisions are now divided into two cases. When $r \leq c$, we have $\gamma^*(\eta|\rho) \leq 1-\rho$ (the equal sign holds only when $r = c$), indicating that the final supply in Zone B never exceeds its demand. This makes sense because a worker still incurs a cost of $c - r$ in relocating to Zone B and thus fewer workers would choose to do so than needed. On the other hand, when the platform offers a bonus higher than workers' relocation cost ($r > c$), we have $\gamma^*(\eta|\rho) > 1-\rho$. In this case, a worker would obtains a higher payoff moving to Zone B than staying in Zone A, resulting in a larger number of movements to Zone B than what it actually needs. Finally, In both cases, $\gamma^*(\eta|\rho)$ is weakly increasing in the regret aversion parameter η, indicating that workers are more likely to relocate to the supply-shortage zone in order to avoid any regretful feeling.

The objective of the platform is to find the optimal bonus in order to maximize its profit. We denote the price that the platform charges its customer as p, and $p > w > c$. In addition to this base price, the platform may also charge customers a price premium if the supply falls short of demand in a particular zone (e.g., the surge pricing adopted by Uber and Lyft). To capture this feature, we assume that the price premium in zone $i \in \{A, B\}$ takes the form of $s(\frac{D_i}{S_i} - 1)^+$ for $S_i > 0$. That is, the price premium takes effect only when demand exceeds supply in a particular zone, and it dynamically changes with the demand-supply ratio. To avoid trivial cases, we assume that $p - s > w + r$. With that, we can obtain the platform's profit function, which is the sum of profits earned in both zones, as:

$$\Pi(\eta|\rho; p, w, s, r) = \left(p + s(\frac{D_A}{S_A} - 1)^+ - w\right)\min(D_A, S_A) + \left(p + s(\frac{D_B}{S_B} - 1)^+ - w - r\right)\min(D_B, S_B).$$

The platform chooses the optimal bonus $r^*(\eta|\rho)$ to maximize its profit[7], given the workers' relocation decisions defined in Equations (5) and (6). That is,

$$\begin{aligned} r^*(\eta|\rho) \quad = \quad & \arg\max_r \left(p + s(\frac{\rho}{1 - \gamma^*(\eta|\rho)} - 1)^+ - w\right) \cdot \min(\rho, 1 - \gamma^*(\eta|\rho)) \cdot n \\ & + \left(p + s(\frac{1-\rho}{\gamma^*(\eta|\rho)} - 1)^+ - w - r\right) \cdot \min(1 - \rho, \gamma^*(\eta|\rho)) \cdot n. \end{aligned}$$

The optimal bonus $r^*(\eta|\rho)$ is characterized by the following theorem. To simplify the presentation, we define $a \equiv p - s - c$.

Theorem 4. *(i)When $c \leq w - \sqrt{wa\rho}$, $r^*(\eta|\rho) = 0$ and the corresponding $\gamma^*(\eta|\rho) > 0$ for all η. (ii) When $c > w - \sqrt{wa\rho}$, there exists two thresholds $\underline{\eta}$=$\max\left(0, \frac{w\rho - a}{a(1-\rho)}\right)$ and $\overline{\eta} = \frac{1}{1-\rho}(\frac{wa\rho}{(w-c)^2} - 1)$ such that*

- *(a) When $\eta \geq \overline{\eta}$, $r^*(\eta|\rho) = 0$, and the corresponding $\gamma^*(\eta|\rho) > 0$;*
- *(b) When $\underline{\eta} < \eta < \overline{\eta}$, $r^*(\eta|\rho) = \min(-w + c + \sqrt{\frac{wa\rho}{1+\eta(1-\rho)}}, c)$, and the corresponding $\gamma^*(\eta|\rho) > 0$; and*
- *(c) When $\eta \leq \underline{\eta}$, $r^*(\eta|\rho) = -w + c + \sqrt{\frac{wa\rho}{1+\eta(1-\rho)}}$, and the corresponding $\gamma^*(\eta|\rho) = 0$.*

Theorem 4 suggests that the platform's optimal bonus offered to workers is dependent on the workers' relocation cost c as well as their regret bias η. When the relocation cost is relatively low ($c \leq w - \sqrt{wa\rho}$), or when the workers are sufficiently regret averse ($\eta \geq \overline{\eta}$), the platform does not need to offer any financial incentive - a sufficient number of workers would choose to relocate to the supply-shortage zone without any bonus. As workers' cost starts to increase, the platform would benefit from offering an incentive bonus to induce extra movement to the supply-shortage zone. However, this extra bonus would not work if workers are not sufficiently averse to regret ($\eta \leq \underline{\eta}$). In that case, workers do not respond to any bonus offered by the platform (i.e., all workers choose to stay in Zone A). Finally, the platform should never offer a bonus higher than workers' relocation cost (i.e., $r^*(\eta|\rho) \leq c$), implying that Zone B remains a supply-shortage zone after the relocation (i.e., $\gamma^*(\eta|\rho) < 1 - \rho$).

We next study how the platform's optimal bonus and the resulting profit change with workers' level of regret aversion.

[7] Since we are interested in workers' behavior, we assume the prices related to demand (p and s) are exogenous. We also assume that the worker's base wage w is fixed since it allows us to focus on the platform's design of optimal bonus r^*, which is a less studied factor in prior research. Our model can be extended to the scenario where the platform jointly decides optimal w^* and r^*. We leave this direction for future research.

Proposition 2. *(i) The optimal bonus $r^*(\eta|\rho)$ is weakly decreasing with η; and (ii) the platform's profit is weakly increasing in η.*

Since workers' aversion to regret causes an extra flow to the supply-shortage zone, the platform could achieve a desired outcome by offering a lower bonus compared to the case of no regret. This low bonus could in turn translate to an increased profit for the platform. Thus, an on-demand platform would never become worse off due to workers' regret-averse behavior.

We then examine whether the platform workers could also benefit from their regret bias. We define the *worker surplus* $\pi(\eta|\rho)$ as the average of the total profit earned by all workers in both zones:

$$\begin{aligned} \pi(\eta|\rho) &= \frac{1}{n}\left[w \min(D_A, S_A) + (w + r^*(\eta|\rho) - c) \min(D_B, S_B)\right]. \\ &= w\rho + (w + r^*(\eta|\rho) - c)\gamma^*(\eta|\rho). \end{aligned} \tag{7}$$

Workers' regret aversion η influences their surplus in both positive and negative directions. On one hand, regret aversion increases the percentage of workers relocating to Zone B (i.e., a higher $\gamma^*(\eta|\rho)$), which leads to an increased worker surplus according to Equation (7). On the other hand, according to Proposition 2, the presence of workers' regret aversion causes the platform to offer a lower bonus, thus reducing worker surplus. As shown in the following proposition, which effect dominates is dependent on the workers' relocation cost c and their level of regret aversion η.

Proposition 3. *(i) When $c \le w - \sqrt{wa\rho}$, or when $c > w - \sqrt{wa\rho}$ and $\eta \ge \bar{\eta}$, worker surplus is strictly increasing in η. (ii) When $w - \sqrt{wa\rho} < c \le p - s - \frac{4\rho}{(1+\rho)^2}w$ and $\eta < \bar{\eta}$, worker surplus is weakly decreasing in η. (iii) When $c > p - s - \frac{4\rho}{(1+\rho)^2}w$ and $\eta < \bar{\eta}$, there exists a threshold $\tilde{\eta}$ such that*

(a) if $\eta < \min(\tilde{\eta}, \bar{\eta})$, worker surplus is weakly increasing in η; and

(b) if $\min(\tilde{\eta}, \bar{\eta}) \le \eta < \bar{\eta}$, worker surplus is strictly decreasing in η.

The insights of Proposition 3 are quite intuitive. First, as suggested in Theorem 4, when the relocation cost is relatively low ($c \le w - \sqrt{wa\rho}$), or when workers are sufficiently regret averse ($\eta \ge \overline{\eta}$), the platform does not offer any bonus. As a result, regret aversion causes more workers to relocate to the supply-shortage zone and thus increases worker surplus. This positive effect also shows up when the relocation is sufficiently high ($c > p - s - \frac{4\rho}{(1+\rho)^2}w$) and when workers are not too averse to regret ($\eta < \min(\tilde{\eta}, \overline{\eta})$). In this situation, the platform must offer a high level of bonus to compensate workers for their high relocation cost, and a small increase in workers' regret bias won't decrease this bonus too much. As a result, the positive effect on worker surplus persists. In contrast, for moderate levels of relocation cost and regret aversion, the platform would instead offer a much lower financial bonus, which reduces workers' total payoff and results in a low level of worker surplus.

Similarly, workers' regret aversion also influences the system's matching efficiency in opposite directions. Recall that the matching efficiency is defined as $M(\eta|\rho) = \frac{D_A+S_B}{n} = \rho + \gamma^*(\eta|\rho)$, which is determined by the relocation equilibrium $\gamma^*(\eta|\rho)$. A higher level of regret aversion not only results in a higher percentage of movement (a direct positive effect), but also results in a lower bonus, which in turn causes fewer workers to move (an indirect negative effect). The overall effect is mixed, which is characterized in the following proposition.

Proposition 4. *(i) When $c \leq w - \sqrt{wa\rho}$, or when $c > w - \sqrt{wa\rho}$ and $\eta \geq \bar{\eta}$, the matching efficiency is strictly increasing in η. (ii) When $w - \sqrt{wa\rho} < c \leq p - s - \frac{(1+\rho)^2}{4\rho}w$ and $\eta < \bar{\eta}$, there exists a threshold $\hat{\eta}$ such that*

(a) if $\eta < \min(\hat{\eta}, \bar{\eta})$, the matching efficiency is weakly decreasing η; and

(b) if $\min(\hat{\eta}, \bar{\eta}) \leq \eta < \bar{\eta}$, the matching efficiency is strictly increasing in η.

(iii) When $c > p - s - \frac{(1+\rho)^2}{4\rho}w$, and $\eta < \bar{\eta}$, the matching efficiency is strictly increasing in η;

The above analysis indicates that regret plays an important role in influencing not only platform's profit but also worker surplus and system's matching efficiency. While the platform always benefit from workers' behavioral bias, the impact on the other two is nuanced. The following corollary provides conditions under which the regret bias could benefit all three stake holders (i.e., the on-demand platform, the workers as well as the whole system).

Corollary 1. *: When (i) $c \leq w - \sqrt{wa\rho}$, or (ii) $c > w - \sqrt{wa\rho}$ and $\eta \geq \bar{\eta}$, or (iii) $c \geq p - s - \frac{4\rho}{(1+\rho)^2}w$ and $\eta \leq \min(\bar{\eta}, \tilde{\eta})$, the platform's profit, worker surplus, and the system matching efficiency are all weakly increasing in η.*

5.2 Experimental Validation

An interesting implication from the above analysis is that workers' behavioral bias due to regret aversion influences how much an on-demand platform should pay its workers for relocation, which could lead to an improved platform profit, worker surplus and overall demand-supply matching efficiency. To further validate this finding, we conduct an experiment to investigate how human participants as platform workers would respond to bonus and whether their decisions are consistent with our theoretical predictions. This experiment is similar to the *Info* treatment described in Section 4.2, plus a bonus paid to the workers in addition to their base wage for serving a customer in the supply-shortage zone. We choose to conduct the experiment only in the high cost ($c = 8$) scenario since, as suggested in Theorem 4, the extra bonus is more likely to be effective when workers' relocation is high.

The optimal bonus level r^* is dependent on the value of workers' regret aversion parameter η (Theorem 4), which we don't know *a priori*. Therefore, we need to first calibrate the value of η using a pre-experiment. In the pre-experiment, we set the bonus level at $\eta = 0$ (i.e., $r^*(0|\rho)$). In other words, we use the optimal bonus if the workers were rational individuals. Even though this bonus is not the optimal value for regret averse workers, it creates a nice "calibration" dataset that enables us to estimate the magnitude of workers' regret aversion. We then use the estimated value of η to calculate the "true" optimal bonus for our main experiment. This approach also allows us to assess the predictive power of our model by comparing theoretical prediction with observed behavior in a new testing dataset. We set the market price $p = 15$ and price premium $s = 1$[8].

We recruited another 100 participants from the same subject pool, with $n = 50$ each in the pre-experiment and the main experiment. Participants were asked to make 40 rounds of the stay-or-move decision. At the beginning of each round, participants observed the demand draw in both zones and the extra bonus they would receive for serving a customer in Zone B. We emphasized the fact that this bonus was only available in Zone B when they fulfilled a customer request. We did not tell our participants how the bonus was calculated but only informed them that the bonus was dependent on the demand state and might change from round to round.

Figure 4a plots the entire 40 rounds of observed percentage of movement to Zone B (dots) against the percentage of workers needed in Zone B (i.e., $1-\rho$) for the pre-experiment. Recall that the workers' bonus in the pre-experiment is set at $\eta = 0$ (no regret). If workers are indeed rational decision makers, we should expect their decisions to be close to the dashed line, which is the rational model prediction assuming $\eta = 0$. It is apparent that majority of the observations are above the dashed line, indicating that workers choose to relocate to the supply-shortage zone more often than predicted by the rational model. This results once again coincides with the regret-averse assumption.

We next use the data from our pre-experiment to calibrate the magnitude of the regret aversion parameter η. We adopt the maximum-likelihood method for model estimation. Since the decision is binary, we assume it follows a Bernoulli distribution. Let y be the decision variable, and y takes the value of 1 if a participant relocates to Zone B, and 0 if staying in Zone A. We can obtain the probability function as:

$$\ell(y) = [\gamma^*(\eta|\rho)]^y \cdot [1 - \gamma^*(\eta|\rho)]^y \quad \text{for } y \in \{0, 1\},$$

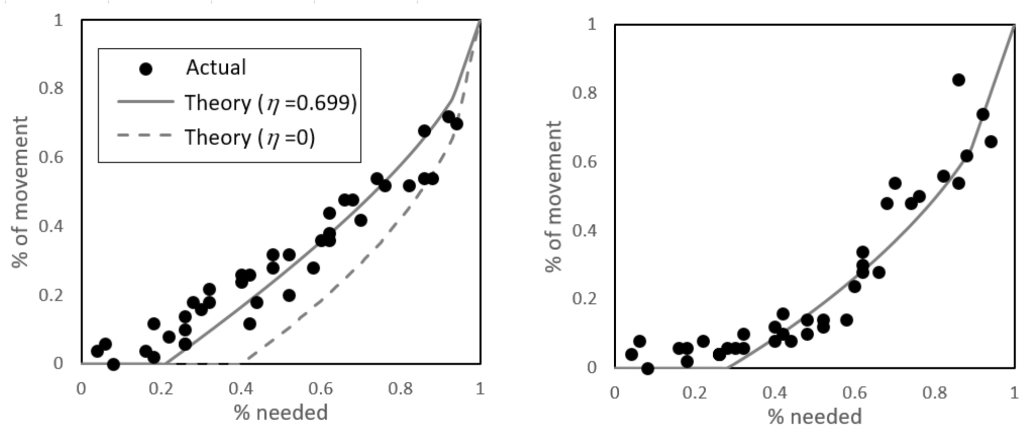
where $\gamma^*(\eta|\rho)$ is workers' relocation equilibrium as defined in Equations (5) and (6). Let $Y = \{y_{it}\}$ be the observed decisions in the pre-experimental data, where y_{it} represents the decision of subject i in round t. Then we have the following likelihood function:

$$L(\eta, \varepsilon) = \prod_i \prod_t \left\{ (1 - \varepsilon) \cdot \ell(y_{it}) + \varepsilon \cdot \frac{1}{2} \right\}.$$

[8]The parameters p and s are only used to calculate the optimal bonus r. In the experiment, we did not inform our participants the value of p and s, since they are irrelevant to their decisions.

Figure 4: Percentage of Movement When Platform Offers Bonus

a) When bonus is $r^*(0|\rho)$ b) When bonus is $r^*(0.699|\rho)$



Note. Each dot represents the observed percentage in one decision round.

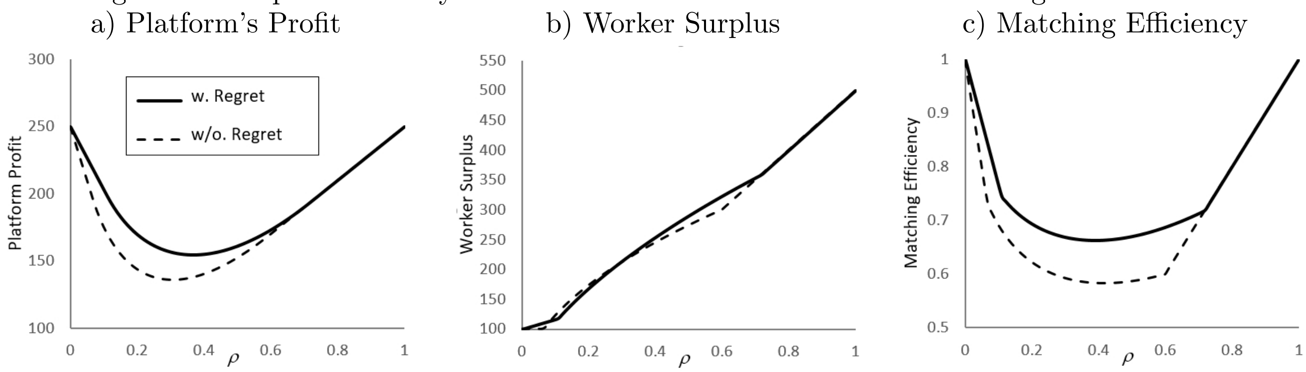
The parameter ε represents an error term; that is, with probability $(1-\varepsilon)$, the worker's decision coincides with our model prediction, and with probability ε, the worker's decision is purely random. In practice, we expect ε to be positive but small. To fit the model, we maximize the likelihood function $L(\cdot)$ over the two parameters η and ε, with the full estimation results reported in the Online Supplement. The estimated regret aversion parameter is $\eta = 0.699$, suggesting that a \$1 forgone loss will impose a \$0.699 physiological cost for not choosing the alternative option. We plot the behavioral response (solid line) in Figure 4a and it fits the data quite well[9].

After calibrating the workers' regret averse level to be $\eta = 0.699$, we calculate the platform's optimal bonus, as established in Theorem 4, and conduct our main experiment using these new values. The observed percentages (dots) are plotted in Figure 4b, along with the behavioral model prediction (solid line). First, compared with the pre-experiment in Figure 4a, the observed percentages to Zone B seem to be lower in the main group. This is sensible because, according to Proposition 2, the platform would offer a lower bonus for regret-averse workers and thus cause workers more likely to stay in Zone A. Second, the observed values are pretty close to the theoretical prediction, indicating that our behavioral model not only fits the data well, but can also accurately predict decisions made by human decision makers who exhibit behavioral tendencies such as regret aversion.

As a final analysis, we performed a numerical simulation to compare the system performances in terms of the platform's profit, worker surplus and matching efficiency with and without regret aversion. In other words, we consider two systems, one in which all the workers are rational individuals who only care about monetary payoffs ($\eta = 0$), and the other with workers who exhibit the behavioral bias of

[9]Note that the solid line represents the decisions made by regret averse workers with $\eta = 0.699$ in response to a bonus level that was set assuming full rationality ($\eta = 0$).

Figure 5: Comparision on System Performance Measures: Rational vs. Regret Aversion



Parameter value: $p = 15$; $s = 1$; $w = 10$; $c = 8$; $\eta = 0$ (dashed line) or η=0.699 (solidline)

regret aversion ($\eta > 0$). This analysis is useful to illustrate the insight obtained from our analytical model that workers' behavioral bias may benefit the whole on-demand system. Using the parameter values used in our experiment, we plot in Figure 5 the three performance measures for the two systems over demand ρ.

Interestingly, both the platform's profit and the matching efficiency reach the highest point when the demand ρ is at the two extreme ends, resulting in a "U" shape (Figure 5a and c). When all the customers are located in one zone (i.e., $\rho = 0$ or $\rho = 1$), workers will also choose that zone because they would not make any earnings in the other zone. In this case, the platform is able to capture the highest profit by achieving 100% matching efficiency. Worker surplus, however, changes monotonically with ρ (Figure 5b). When ρ is small (i.e., demand in Zone B is high), workers are willing to incur relocation costs and move to the supply-shortage zone. In this case, worker surplus is reduced because of the incurred cost. As ρ increases, workers are less likely to relocate to Zone B, leading to an increased worker surplus.

Finally, when comparing the performance measures between the two systems with (solid line) and without (dashed line) regret, we find that regret aversion does not play a role if the customer demand in Zone A is sufficiently high ($\rho > 0.72$ in our data). In this case, no workers are willing to relocate to Zone B, and thus the two systems yield the same performance. However, when the demand in Zone A is not quite high ($\rho < 0.72$), the platform can always benefit from regret averse workers by receiving a higher profit (Figure 5a) as well as achieving a better efficiency of matching supply with demand (Figure 5c). In additional, platform workers may also take advantage of their own regret-averse behavior and obtain a higher level of surplus in most of the demand cases except when ρ is between 0.09 and 0.27 (Figure 5b). In summary, our numerical analysis provides further support for the theoretical findings that workers' aversion to regret can indeed benefit the on-demand sharing business.

6 Conclusion

Research that studies policies in on-demand platforms has been normative in nature. These studies are often under the assumption that workers are rational agents who are able to calculate the optimal solutions. However, it is well acknowledged that humans are not rational; their decisions are subject to behavioral biases. Our research thus fills a much-needed gap in the sharing economy literature by investigating human workers' decision from a behavioral perspective.

Using a combination of behavioral modeling and controlled lab experiments, we uncover two behavioral tendencies that influence workers' decisions in an on-demand platform setting. First, workers may feel regret if their (*ex post*) decision does not lead to an anticipated outcome. This behavioral tendency of regret aversion causes workers more likely to relocate to the supply-shortage zone than the case of no regret. Second, to improve the matching efficiency of the on-demand platform, we consider two communication mechanisms, demand information sharing and suggestion provision. While standard model predicts that suggesting a concrete action to workers should be more effective than sharing demand information, we observe opposite results in our experiments, indicating that workers can better utilize the demand information, but tend to ignore suggestions provided by the platform. We further find that workers' ignorance of suggested actions is due to their inability to perform demand update based on the received suggestion.

Our experimental results suggest that, when relocation cost is relatively low, providing workers with demand information can sufficiently improve system performance, achieving a 94% matching efficiency. However, when relocation cost is high, information sharing alone is not sufficient to achieve a high matching efficiency. Consequently, in order to incentivize an adequate amount of workers to move to the supply-shortage zone, the platform may need to offer an extra financial payment to compensate for workers' high relocation cost. We study how the platform should set the optimal bonus and how workers' behavioral tendency of regret aversion influences the on-demand system's performance. We find that under certain conditions, workers' regret aversion can simultaneously increase the platform's profit, worker surplus, and the overall matching efficiency. These results illustrate that workers' irrational behavior such as regret aversion can actually benefit the on-demand sharing business.

Our research highlights the importance of incorporating worker's behavioral biases in the context of on-demand platform. We illustrate that theories without incorporating these biases may yield inaccurate predictions, and thus lead to suboptimal decisions. Consequently, future research should take into consideration the platform workers' behavior biases and design better policies to increase platform's revenue and benefit the entire society.

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