INFORMATION SHARING AND OPERATIONAL TRANSPARENCY ON ON-DEMAND SERVICE PLATFORMS

A Dissertation
Presented to
The Academic Faculty

By

Swanand Kulkarni

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
Scheller College of Business
Operations Management Department

Georgia Institute of Technology

August 2023

INFORMATION SHARING AND OPERATIONAL TRANSPARENCY ON ON-DEMAND SERVICE PLATFORMS

Thesis committee:

Dr. Basak Kalkanci (Advisor)
Scheller College of Business
Georgia Institute of Technology

Dr. Chris Parker
Kogod School of Business
American University

Dr. Ravi Subramanian
Scheller College of Business
Georgia Institute of Technology

Dr. Beril Toktay
Scheller College of Business
Georgia Institute of Technology

Dr. Manpreet Hora
Scheller College of Business
Georgia Institute of Technology

Date Approved: July 12, 2023

ACKNOWLEDGMENTS

I would like to express my sincere appreciation towards my dissertation committee. Firstly, I am extremely grateful to my PhD Advisor, Dr. Basak Kalkanci, for her guidance and support throughout this journey. Her keen involvement in my progress and her persistent encouragement has helped me tremendously to improve overall as an academic. Thank you so much for believing in me and providing me with opportunities for growth. I am also deeply thankful for the support I received from Dr. Chris Parker, Dr. Ravi Subramanian, Dr. Beril Toktay, and Dr. Manpreet Hora. Chris, thank you for your unique perspective and contribution towards our collaboration, for your active support during my job market, and for introducing me to countless people in the field. Ravi, I have learned a lot from observing your teaching when I was your TA, and I will carry that with me for the future. Thank you for your support during my job market and for being easily available to provide your advice whenever I needed it. Beril, getting advice from you before my job market helped me tremendously during my interviews. Thank you for your active involvement in the progress of my research and my job search. Manpreet, your guidance, and support initially during my PhD made settling into the program very smooth. Thank you for your cheerful conversations and for always being keenly interested in my progress.

I also want to thank faculty and fellow PhD students in the Operations Management group. Thanks to all faculty members, who have always been encouraging and supportive—professionally, and otherwise. Special thanks to my PhD colleagues, who have all helped me in numerous ways. I look up to each of them and root for their continued success. To Zeya, Li, and Chris, with whom I shared this PhD journey, thank you for always being there to help and for your comforting friendship. Thanks to the PhD students in the program senior to me when I joined, Shubho and Param, who helped me navigate and settle into the program. To Shikha, Abhinav, and Daniel, thank you for your cheerful company and friendship.

I am deeply thankful to the friends that I have had the fortune of making during my time in Atlanta. Thank you for making me feel supported in a new country, which has greatly helped me in aspiring for and going through my PhD: Aman Namdeo, Geet Lahoti, Jordan Herring, Aditya Bhatambrekar, Baridhi Malakar, Shikha Safaya, Abhinav Shubham, Zeya Wang, Li Ding, Chris Green, Shubham Jamdade, Mrunmai Niljikar, and Shradha Singh.

I would like to thank my alma mater, Visvesvaraya National Institute of Technology Nagpur, for providing me with an environment that prepared and motivated me to work towards my ambitions. Sincere thanks to Prof. Vishal Gupta at IIM Ahmedabad, Dr. Matthias Seifert at IE Business School, and Dr. Shatakshee Dhongde for helping me find my way towards the PhD program in Operations Management. I am also deeply grateful to Georgia Tech for providing the best nurturing environment that I could have had.

I would like to thank and dedicate my dissertation to my late maternal grandfather, and my paternal grandfather—both of whom devoted their sincere service to academia. Their loving encouragement helped me believe in myself. I am grateful to all my family members for supporting my decisions, and without whom, I could not have accomplished the goal of pursuing a PhD. Sincere thanks to my close friends in India for helping me stay close to my roots during this highly dynamic phase of my life. Finally, I would like to convey my appreciation towards Gargi Deshpande, whose unwavering support made my transition to a new country feel significantly easier.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

The three essays in this dissertation examine the operational practices of on-demand service platforms, pertaining to information sharing and operational transparency on the supply-side. On-demand service platforms such as ridesharing, food delivery, grocery delivery, and courier delivery platforms critically depend on the services of workers, who are independent contractors. Given that these workers have discretion over their labor supply decisions, the platform's information provision to workers plays a key role in influencing workers' decisions and in eventually meeting the customer demand. In this dissertation, I employ game-theoretic modeling and conduct incentivized experiments with human subjects to evaluate the implications of a platform's practices around information sharing and operational transparency with workers, for workers' decisions and potentially for the platform's operational outcomes.

Demand-Supply Information Sharing: We investigate how an on-demand service platform's mechanism to share demand–supply mismatch information spatially affects drivers' relocation decisions and the platform's matching efficiency. We consider three mechanisms motivated by practice: the platform either shares demand–supply mismatch information about zones(s) with excess demand (i.e., surge zone(s)) with all drivers (surge information sharing, common practice today), all zones with all drivers (full information sharing), or about surge zone(s) only with drivers sufficiently close by (local information sharing). We develop a game-theoretic model with three zones; drivers in two non-surge zones decide whether to relocate to the surge zone. We incorporate two spatial aspects: drivers' relocation costs, and initial supply across non-surge zones. Theoretically, full can yield a lower matching efficiency than surge information sharing under low relocation costs because drivers do not relocate as much when demand in non-surge zones is high. Local information sharing is strictly dominated by other mechanisms on matching efficiency under limited supply near the surge zone, and weakly dominated otherwise by surge information sharing. We test these theoretical predictions in the lab with human participants as drivers. Experimentally, surge information sharing serves fewer customers than predicted because drivers relocate too often,

compromising efficiency in the non-surge zones. The alternatives, full and local, are not dominated by surge information sharing, and serve more customers than theoretically predicted—providing support for their potential benefits. A behavioral equilibrium incorporating loss aversion through mental accounting and decision errors describes drivers' behavior in our experiments better than the rational equilibrium.

Payment Algorithm Transparency: On-demand service platforms have been experimenting with algorithms to determine compensation for their workers. While some use commission- or effort-based algorithms that are intuitive to workers, others, in their efforts to better match customer demand, have transitioned to algorithms where pay is not strictly tied to effort, but depends on other, potentially exogenous factors. Platforms have also kept these algorithms opaque. Despite the move towards less-intuitive and opaque algorithms in practice, workers' reactions to them are not systematically examined or understood. Through incentivized online experiments on Prolific, we present real-effort tasks as work opportunities for payment to human participants, and examine how individual features of a pay algorithm, specifically its intuitiveness to workers and transparency, affect workers' engagement (measured by work rejection rates and willingness to pay to accept a work opportunity) and perceptions of the platform. We also examine the effect of an algorithm change from intuitive to non-intuitive, and how transparency interacts with this change. For workers with prior experiences on the platform, intuitiveness, and transparency both are effective at sustaining engagement in our experiments. Transparency is particularly motivating for workers under a non-intuitive algorithm and can fully compensate for the reduction in worker engagement from implementing a non-intuitive algorithm. Furthermore, even though a transparent platform experiences a drop in worker engagement after switching to a non-intuitive algorithm, commitment to transparency is still beneficial: Worker engagement with transparency is at least as much as that without transparency, while transparency is more potent at motivating positive perceptions towards the platform.

Platform Commission Transparency: On-demand service platforms in the role of an intermediary that matches service-seeking customers and service-providing independent contractors, typically charge workers a commission on each service request that they complete. Early on, most on-demand service platforms operated a fixed commission model, where the platform determines the price on a service request such that the worker completing it is compensated for effort, while the platform keeps a fixed percentage of the price as a commission from the worker. While several platforms continue to operate this model, some platforms transitioned to a model where the platform's commission is inconsistent across service instances. Thereby, while the platform continues to compensate workers based on effort-based factors, it utilizes several factors that do not influence workers' wage to determine the price—leading to the platform commission being variable across service instances. Platforms argue that this helps to improve customers' experience through better prices while drivers continue to earn for their effort. Anecdotal evidence suggests that workers are concerned about the large commission that platforms charge them in some service instances. In response, platforms have experimented with workers' visibility of the platform's commission under the variable commission model—which has reportedly contributed to worker suspicion and distrust. Motivated by these practices, we design incentivized experiments with human subjects to examine the influence of a platform's commission on workers' participation decisions under the fixed and variable commission models. We study the impact of consistency in platform commission on workers' participation decisions and their perceptions of the platform. Furthermore, we evaluate how the visibility of platform commission influences workers' participation decisions and their perceptions of the platform.

CHAPTER 1
INTRODUCTION

On-demand service platforms such as ridesharing, food delivery, grocery delivery, and courier delivery platforms have recently grown to become a major part of the service economy. Problems pertaining to the management of such platforms' operations have gathered significant interest from researchers. One of the features of such platforms that makes their operations challenging is the fact that service-providers on such platforms are not employees but are independent contractors who exercise significant freedom in their labor supply decisions. Given such worker discretion, levers such as information sharing and operational transparency play a key role in influencing workers' utility and their decisions on the platform, and eventually the platform's ability to match demand and supply. Three essays in this dissertation investigate such effects. By employing game-theoretic and experimental techniques, we examine how a platform's information sharing and operational transparency with workers influences workers' decisions and potentially the platform's operational outcomes.

In Chapter 2, titled "*Spatial Information Sharing on On-Demand Service Platforms: A Behavioral Examination*", we examine how an on-demand service platform's mechanism to share demand–supply mismatch information spatially, affects drivers' relocation decisions and the platform's ability to match demand and supply. We focus on three mechanisms motivated by practice: the platform either shares demand–supply mismatch information about zones(s) with excess demand (i.e., surge zone(s)) with all drivers (surge information sharing, common practice today), all zones with all drivers (full information sharing), or about surge zone(s) only with drivers sufficiently close by (local information sharing). We build a game-theoretic model to study drivers' relocation decisions under competition, and the platform's resultant matching efficiency in equilibrium. Drivers in two non-surge zones decide whether to relocate to the surge zone, under heterogeneity in relocation costs and initial supply across non-surge zones. In theory, full information sharing can yield a lower matching efficiency than surge information sharing under low relocation costs because drivers do not relocate as much when demand in non-surge zones is high. Local information sharing is strictly dominated by other mechanisms in matching performance when the supply near the surge zone is limited, and weakly dominated otherwise by surge information sharing. These predictions serve as our hypotheses that we test in the lab with human participants as drivers. In our experiments, surge information sharing serves fewer customers than predicted because drivers relocate too often, hurting the efficiency in the non-surge zones. Its alternatives, full and local, are not dominated by surge information sharing, and yield greater matching efficiency than theoretically predicted—providing support for their potential benefits. A behavioral equilibrium that incorporates loss aversion through mental accounting and decision errors describes drivers' behavior in our experiments better than the rational equilibrium.

In Chapter 3, titled "*Payment Algorithm Transparency on On-Demand Service Platforms*", we examine how the features of an on-demand service platform's payment algorithm that determines workers' earnings influence workers' engagement with the platform and their perceptions of the platform. Practical observations pertaining to payment algorithms indicate that some platforms use commission- or effort-based algorithms that are intuitive to workers. In contrast, others, in their objective to better match customer demand, have transitioned to algorithms where pay is not strictly tied to effort, but depends on other, potentially exogenous factors. Platforms have also kept these algorithms opaque. Despite the move towards less-intuitive and opaque algorithms, workers' attitudes towards them are not systematically examined or understood. Through incentivized online experiments on Prolific, we offer real-effort tasks as work opportunities for payment to human subjects. We examine how individual features of a pay algorithm, specifically its intuitiveness to workers and transparency, influence workers' engagement (measured by work rejection rates and willingness to pay to accept a work opportunity) and perceptions of the platform. We also examine the impact of an algorithm change from intuitive to non-intuitive, and the role of transparency in managing it. For workers with prior experiences on the platform, intuitiveness and transparency both are influential in sustaining engagement in our experiments. Transparency is particularly motivating for workers under a non-intuitive algorithm and can fully overcome the loss in worker engagement from implementing a non-intuitive algorithm. Moreover, although a transparent platform experiences a reduction in worker engagement after transitioning to a non-intuitive algorithm, it is still beneficial to commit to transparency: Worker engagement under transparency is at least as much as that under opacity, while transparency is more potent at motivating positive perceptions towards the platform.

In Chapter 4, titled "*Platform Commission and its Transparency on On-Demand Service Platforms*", we focus on an on-demand service platform's practices pertaining to how it determines its commission and its transparency to workers. Platforms, particularly those offering ridesharing services, typically charge the workers a commission on each service request that they complete. Platforms have been experimenting with how they determine their commission. Initially, most on-demand service platforms operated a fixed commission model, wherein the platform determines the price on a service request such that the worker completing it is compensated for effort, while the platform keeps a fixed percentage of the price as a commission from the worker. However, some platforms subsequently transitioned to a variable commission model. Under this practice, while the platform continues to compensate workers based on effort-based factors, it utilizes several factors that do not influence workers' wage to determine the price. This results in the platform commission being variable across service instances. Platforms cite that by doing so, they can improve customers' experience through better prices, while drivers continue to earn for their effort. However, anecdotal evidence suggests that workers object to the higher commission that the platform might charge in some service instances. In response, platforms have experimented with workers' visibility of their commission under the variable commission model. However, the opacity has reportedly contributed to worker suspicion and distrust. Motivated by these practices, we design incentivized experiments with human subjects to systematically examine the effect of a platform's commission on workers' participation decisions under the fixed and variable commission models. We study the impact of consistency in platform commission on workers' participation decisions and their perceptions of the platform. Moreover, we evaluate how the visibility of platform commission influences workers' participation decisions and their perceptions of the platform.

CHAPTER 2

SPATIAL INFORMATION SHARING ON ON-DEMAND SERVICE PLATFORMS: A BEHAVIORAL EXAMINATION

2.1 Introduction

In recent years, the gig economy has redefined the ways in which many economic transactions in the market work, with a platform connecting service-seeking customers with service-providing agents being at the center of most of these business models. Of particular interest are the on-demand service platforms like ride-sharing and food-delivery apps. Platforms like Uber, Lyft, DiDi, Bolt, and many others, that match ride-seeking customers with ride-providing agents, have now taken the foreground, even surpassing regular taxis in pickups in New York City in 2017 (Wagner 2018). In a traditional taxi setting, drivers must rely on their own knowledge of customer demand in various parts of the city to search for riders, which is often tedious and inefficient. By utilizing aggregate information about ride-seekers and ride-providers, ride-sharing platforms reduce this search cost for drivers and utilize capacity more efficiently than traditional taxis (Cramer and Krueger 2016).

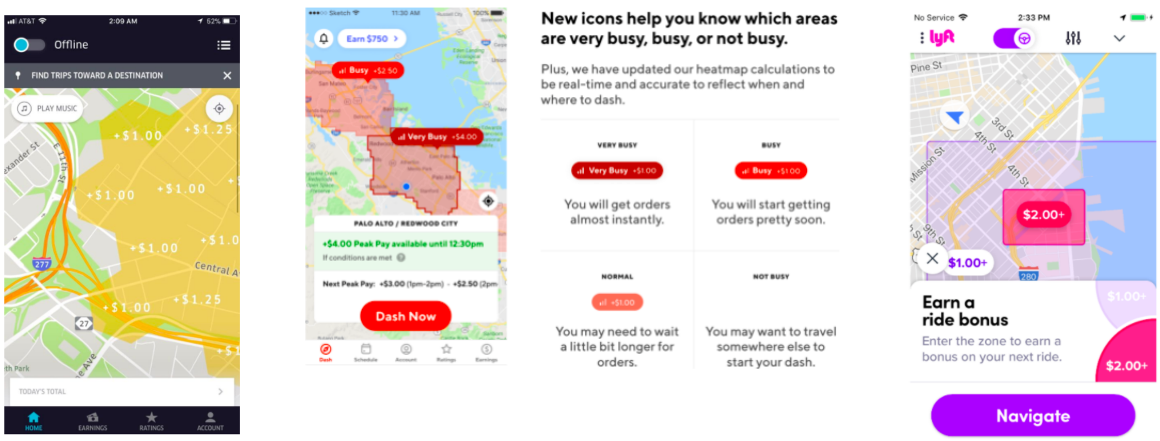
A characteristic feature of most of these platforms is that the agents are independent; they are free to provide service when and where they like. On-demand service platforms with independent service providers often face the problem of demand and supply mismatch because, in addition to demand, capacity available on the platform at any given time and location is uncertain. As such, the platform has to signal the need for supply to its independent agents, and the performance of a platform depends to a great extent on how effectively this interaction with drivers is managed.

For signaling supply needs, platforms commonly engage in dynamic (or surge) pricing, increasing prices when and where demand exceeds supply. This way, the platform attempts to satisfy the excess demand in a geographic region, mainly by attracting drivers from regions of excess supply and incentivizing them to relocate (Chen et al. 2015; Diakopoulus 2015). With surge pricing, the price in a region reflects the underlying demand *relative* to the supply in the region (Chen et al. 2015; Lu et al. 2018). Hence, along with providing direct incentives, platforms can use surge pricing maps to communicate demand–supply mismatch information about different regions with drivers.

Different platforms have implemented different forms of sharing demand–supply mismatch information spatially with drivers. The prevalent format, which many platforms such as Uber, Via, Ola, DiDi, Cabify, Bolt, Postmates, and Grubhub use, involves sharing the demand–supply mismatch information for only those regions where demand exceeds supply. For example, Uber's heat maps highlight regions where demand exceeds supply, which are called *surge zones*, while providing no explicit feedback on the conditions in other zones (Figure 2.1a). That way, they influence drivers' location decisions and attract them towards areas with greater demand relative to supply (Lu et al. 2018). We refer to this as *surge* information sharing. Despite its prevalence, surge information sharing has also been criticized for resulting in "flocking," which involves too many drivers in non-surge zones moving towards surge zones (Gridwise 2017). This flocking behavior can potentially reduce earning opportunities for drivers in surge zones and create dissatisfaction, which is manifested in the popular opinion among some drivers that surges should not be chased (Campbell 2016).

Concurrently with the ongoing discussion on the efficacy of surge information sharing, some platforms have implemented alternative spatial information-sharing mechanisms. For example, DoorDash has adopted a related, but more detailed mechanism: On their app, drivers observe demand–supply mismatch information about both surge and non-surge zones[1] (Figure 2.1b). We refer to this as *full* information sharing. For both surge and full information sharing, the demand–supply mismatch information is shared publicly, meaning that all drivers have access to the same information. More recently, however, private and more personalized information-sharing mechanisms have been introduced. For example, Lyft recently introduced Personal Power Zones, partly

[1] Grab follows a similar practice: https://www.grab.com/my/blog/driver/improved-heat-map/



(a) Uber's Heat Map (b) DoorDash's Hot Maps (c) Lyft's Personal Power Zones

Figure 2.1: Different demand–supply mismatch information-sharing mechanisms. Source: (a) Gridwise (2018) (b) Doordash (2020) (c) Hub (2019)

Note: (a) Regions in need of drivers show bonuses reflective of underlying levels of demand–supply mismatch. (b) Regions are marked as very busy, busy, normal, or not busy for drivers based on the demand-supply mismatch levels. (c) Surge in a region is visible only to drivers in close proximity.

to provide drivers with a "more reliable" way to find demand opportunities (Ong et al. 2021), as an alternative to its Prime Time feature which was similar to surge information sharing (Helling 2023). With this new mechanism, the platform shares information about a surge zone only with drivers sufficiently close by (see Figure 2.1c), as opposed to sharing information on conditions throughout the city (Hub 2019). We refer to this as *local* information sharing. Despite the variety of information-sharing mechanisms implemented by different platforms, it is not clear which one would be most effective at aligning driver behavior with system-wide service requirements.

In designing the strategy to share spatial demand–supply mismatch information with drivers, a platform faces non-trivial theoretical and behavioral trade-offs: For example, highlighting surge zones only can motivate drivers located in non-surge zones to focus on and pursue opportunities outside their own zones, which can help the platform match the surge demand more effectively and serve more customers overall. This mechanism, however, can also contribute to "flocking" as discussed above, presumably by making earning opportunities in surge zones highly salient. Sharing demand–supply mismatch information on both surge and non-surge zones (as DoorDash does) allows drivers to compare potential earnings in different zones more precisely, and make more informed decisions about where to serve. However, if drivers' incentives are not fully aligned with the platform (for example, due to high real or opportunity costs of relocating to another zone), providing extensive information about all zones rather than highlighting the surge only can result in unmet surge demand, thereby reducing platform efficiency. Furthermore, sharing information locally (as in Lyft's Personal Power Zones, a private information-sharing mechanism) can alleviate flocking by reducing the number of drivers who are informed about a surge, and potentially reduce excessive driver competition in high surge conditions that tends to hurt both the drivers and the platform. But this limited information sharing will only be attractive from the platform's perspective as long as the platform is able to attract a sufficient number of drivers to a surge zone. These theoretical and behavioral trade-offs have not yet been examined extensively in the literature, which is the focus of this paper.

Examining these trade-offs in spatial information-sharing mechanisms are important for a variety of diverse stakeholders. Such mechanisms affect a platform's ability to match demand with supply, driver earnings, and customer satisfaction. Moreover, since the platform's ability to meet the customer demand and the associated wait times for customers are likely to affect the customer engagement with the platform, spatial information sharing is expected to be highly influential on the platform profitability over the long run. Finally, drivers' relocation can burden road traffic, and is hence of concern to road-transportation authorities as well (Fen-Cheng 2019; Jha et al. 2018).

Given these considerations, we aim to answer the following research questions in this paper: (1) Which of the three spatial information-sharing mechanisms should a platform use to maximize its matching efficiency, as measured by the proportion of service requests satisfied? Should a platform share demand–supply mismatch information about surge zones only (surge), about all zones (full), or should the platform follow a more personalized information-sharing approach (local) by highlighting surge zones only for drivers nearby? Under what conditions? (2) How do drivers' behavioral influences affect their relocation decisions and the matching efficiency under the three spatial information-sharing mechanisms, and the platform's choice among them?

To answer these research questions, we first develop a stylized game-theoretic model for drivers' relocation decisions. In our model, there are three zones, one of which faces a shortage of supply, while the other two zones are not surging initially. Drivers in the non-surge zones decide whether to relocate to the surge zone by incurring a cost, or to stay in their respective zones. Drivers in the two non-surge zones face different relocation costs and these two zones may also initially have different levels of supply. Based on drivers' decisions, supply is rebalanced in the system and each driver is assigned a ride or not depending on the supply and demand conditions in the zone the driver ends up in. We characterize drivers' relocation decisions and the matching efficiency in equilibrium under the three information-sharing mechanisms (surge, full, local). We then turn to laboratory experiments to test model predictions and identify drivers' behavioral influences for a complete examination of the three information-sharing mechanisms. In our experiments, human participants play the role of drivers, who are randomly assigned to a non-surge zone initially and simultaneously make relocation decisions over multiple periods.

Theoretically, we find that sharing the demand–supply mismatch information about all zones (full) can hurt platforms' matching efficiency compared to sharing information about the surge zone only (surge), particularly when drivers' relocation costs are low. This is because with full information sharing, drivers in non-surge zones, facing high demand in their own zones, choose not to chase the surge, which can hurt the overall efficiency. Interestingly, we find limited value for local information sharing (local) in theory: Local information sharing is strictly dominated by full or surge information sharing when the supply of drivers is limited near the surge region, and otherwise, surge information sharing is expected to perform at least as well. We test these predictions in the lab in an experimental environment with low relocation costs and limited supply of drivers nearby the surge region, wherein matching efficiency is predicted to be highest with surge information sharing and lowest with local information sharing.

In the light of these theoretical predictions and the predominance of surge information sharing in practice, our experiments reveal two key insights: (i) The platform serves fewer customers than theoretically predicted with surge information sharing, and (ii) the two alternative mechanisms, full and local information sharing, serve more customers than theoretically predicted and perform at least as well in matching efficiency as surge information sharing. Consistent with observations from practice, we find that drivers particularly from nearby zones chase the surge too often under surge information sharing. This results in a significant loss of efficiency in the non-surge zones which cannot be recovered despite a greater matching performance in the surge zone. Using Maximum Likelihood Estimation, we find evidence that deviations in drivers' relocation behavior from theory can be described by their loss aversion through mental accounting and their susceptibility to decision errors. Therefore, the platform can better predict the availability and movements of drivers across zones by incorporating these behavioral tendencies.

The rest of the paper is organized as follows. In section 2.2, we discuss relevant work from literature. We introduce our model for drivers' relocation decisions in section 2.3. In section 2.4, we characterize the equilibrium conditions under the three information-sharing mechanisms and compare these mechanisms in terms of overall expected matching efficiency. In section 2.5, we describe our experimental design, and we discuss our experimental results in section 2.6. We propose a behavioral model to explain our experimental findings in section 2.7. We conclude in section 2.8.

2.2 Related Literature

Broadly, our work is related to literature in Operations Management (OM) on on-demand service platforms. Early research in this area focused on platforms' decisions on pricing, setting wages, and hiring capacity (Cachon et al. 2017; Gurvich et al. 2019; Hu and Zhou 2020; Bai et al. 2019; Chen and Hu 2020; Taylor 2018). In modeling drivers, the emphasis in these papers is on drivers' decisions to join the platform and when to provide service in a particular region, and thus, drivers' movements across regions were not considered.

A growing body of literature has recently started to analyze operational decisions of platforms serving multiple regions. Besbes et al. (2021) consider how a ride-hailing platform should set prices for different locations in the short-run, facing a fixed set of drivers that choose where to relocate based on prices, travel costs, and driver congestion levels. Bimpikis et al. (2019) consider a ride-sharing platform that serves a network of interconnected locations wherein drivers decide whether and where to enter the platform, and where to relocate to when idle. Afeche et al. (2022) evaluate the performance of supply-side capacity repositioning control, where a platform serving a network of locations can direct drivers to go where they are needed most. Hu et al. (2022) study surge pricing under the temporal characteristic that drivers are slower to respond to surge pricing than riders. They consider a single location that experiences demand surge, but drivers located elsewhere can chase the surge at a cost. Guda and Subramanian (2019) study when, why, and where a ride-sharing platform informed about the demand forecast and supply conditions would benefit from implementing surge prices. They find that the platform can benefit from choosing a surge price in a non-surge zone—by reducing the potential earnings for drivers in that zone and inducing more drivers to move to a zone that will surge in the future. For a more detailed review of literature on models with spatial considerations, we refer the reader to Hu et al. (2022) and references therein. In all of the aforementioned papers, drivers are fully informed about the prices and wages in all zones, which are informative about the underlying demand–supply mismatch in these zones. However, previous work has not explicitly considered spatial variations in the information available to drivers on market conditions and/or surge pricing, which is the main focus of this paper.

Our work also contributes to a growing body of empirical research that explores the relationship between platforms' levers such as spatial pricing and/or information sharing and drivers' movements. Lu et al. (2018) study the impact of surge pricing on drivers' relocation decisions. Using data from UberX, and a difference-in-difference analysis on an outage of Uber's heat-maps for iOS users, they report that the lack of visibility of heat maps caused drivers to be less sensitive to differences in surge prices and their earnings to decline. Chen et al. (2015) find that Uber's drivers are heterogeneous in their response to surge pricing—sometimes drivers drive into the surge zone; sometimes they move away from it thinking that high prices would mean less customers. Karacaoglu et al. (2018) use data from a taxi company that provided drivers the visibility over the movements of other drivers on its app, to examine drivers' responses to the movement of their peers. They find that drivers respond to more drivers entering their region, mainly by moving out of it. Jiang et al. (2021) demonstrate through laboratory experiments that drivers exhibit regret aversion in their relocation decisions, with regret-averse drivers being more willing to relocate to zones with supply shortages. The paper then considers how, faced with drivers' regret aversion, the platform should use demand information sharing and bonuses to incentivize relocation and increase its matching efficiency. In contrast to prior literature, our work is unique in comparing different information-sharing mechanisms (through variations in surge maps) which reveal demand–supply mismatch information at different levels of granularity for different locations. Furthermore, our experimental approach allows us to disentangle the effect of information-sharing mechanisms from potentially unobserved factors, such as the drivers' prior knowledge about demand and supply conditions or the demand conditions in real time.

Our work is also related to the literature in information design, where the principal designs optimal mechanisms to signal information to agents. Yang et al. (2019) examine algorithmic approaches to compute optimal mechanisms for a principal to signal its private information either publicly to all agents or through private messages to each agent, in settings with resource competition and negative externalities among agents. In contrast, our focus is on the comparison of spatial information-sharing mechanisms observed in practice through analytical modeling as well as laboratory experiments, which takes drivers' behavior into account explicitly. Moreover, we focus on a specific form of a private information-sharing mechanism motivated by practice wherein the demand–supply mismatch in a surge region is revealed only to the nearest drivers.

Lastly, our work is related to the literature on information sharing in OM, particularly to supply chain settings where a downstream firm shares market information (such as the demand forecast) with upstream firm(s) (Lee et al. 2000; Cachon and Fisher 2000; Lee and Whang 2000; Gavirneni et al. 1999; Li 2002; Gaur et al. 2005; Chen and Lee 2009; Cui et al. 2015). Our work is differentiated by the distinctive characteristics of the on-demand service platform context—most notably, the spatial nature of demand and supply faced by the platform, and the drivers' ability to choose which region (i.e., market) to serve in.

2.3 Model Formulation

We consider an on-demand service platform that operates in a market consisting of three zones, which represent different geographical regions. The platform receives service requests in each zone, which we refer to as the *customer demand*, and aims to fulfill those requests as soon as possible by assigning each request to a driver available in that zone. Initially, a fixed number of drivers is available in each zone; however, the platform utilizes dynamic pricing and information sharing on market conditions to motivate those drivers to relocate in order to match supply and demand across all zones more effectively.

We consider three different formats for sharing demand–supply mismatch information by the platform. We define demand–supply mismatch as the difference between demand and supply. The platform is either committed to sharing information about (i) the magnitude of demand–supply mismatch solely in a surge zone (where demand exceeds supply) with all drivers (*surge* information sharing); (ii) the magnitude of demand–supply mismatch in all three zones with all drivers (*full* information sharing); or (iii) the magnitude of demand–supply mismatch solely in a surge zone but only with drivers sufficiently close by (*local* information sharing). Since sharing misleading information will have negative consequences for the platform in the long run, we focus on truthful information sharing by the platform.

The sequence of events for the platform and drivers is depicted in Figure 2.2. First, in Stage 1, the uncertain customer demand is realized in all three zones and the platform shares demand–supply mismatch information with drivers according to its pre-committed format as summarized in Table 2.1. Then, each driver determines whether to *stay* and continue to seek customers in his current zone, or to *move* to a different zone to seek customers by incurring a positive relocation cost. If drivers choose to move to a different zone, they are no longer available to serve customers in their initial zone. Next, the platform matches the customer demand in each zone with the drivers that have chosen to stay in that zone. Relocating to another zone or fulfilling a customer request each takes the entire duration of Stage 1 for a driver. Stage 2 proceeds similarly to Stage 1, with

Table 2.1: Information structure for Stage 1

Mismatch Information Available to Drivers in:	**Full Information**			**Surge Information**			**Local Information**		
	Zone 1	Zone 2	Zone 3	Zone 1	Zone 2	Zone 3	Zone 1	Zone 2	Zone 3
Zone 1	✓	✓	✓			✓			
Zone 2	✓	✓	✓			✓			✓
Zone 3	✓	✓	✓			✓			✓

the exception that the customer demand in each zone is now matched with an updated driver pool, which includes both the drivers that have chosen to stay in that zone in Stage 1 as well as those (if any) that have chosen to relocate to that zone from other zones.

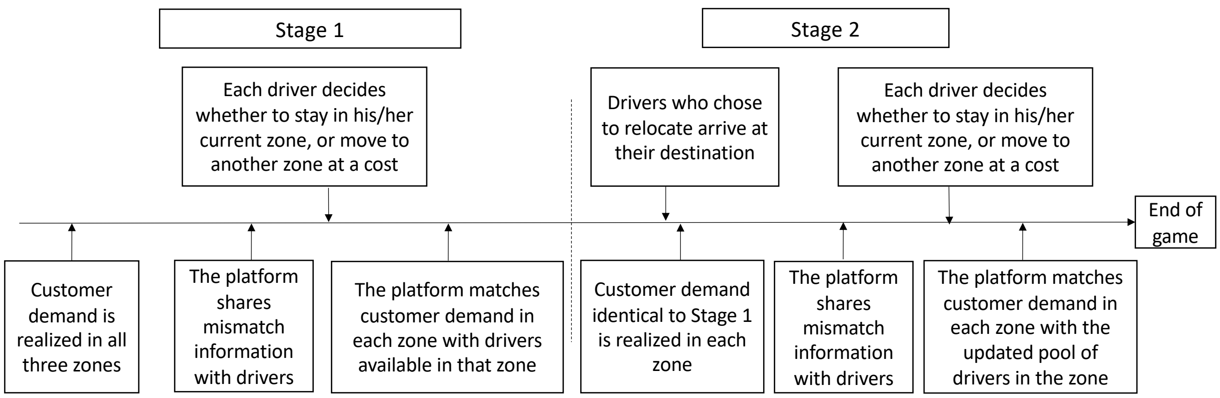


Figure 2.2: Sequence of events

Demand in Zone $j \in \{1, 2, 3\}$ in Stage 1 is represented by the random variable D_j, which follows a Uniform distribution $U[0, n]$. The demand across all zones is independent and identically distributed[2]. Since stages 1 and 2 represent two close points in time, we assume for tractability that the demand in Stage 2 in Zone j is equal to the realized Stage 1 demand $D_j = d_j$ of that zone. The demand distribution in each zone is common knowledge among all drivers; however, a driver does not observe the realized demand in a particular zone if that information is not made available by the platform.

There is a spatial imbalance of supply across the zones prior to Stage 1, with Zones 1 and 2

[2]This allows us to analyze a setting in which a driver's knowledge of the demand–supply conditions in one zone is the *least* informative about the other zones. As a result, information-sharing mechanisms are more likely to influence drivers' relocation decisions and the differences between these mechanisms are more meaningful. This is also consistent with the primary purpose of spatial information sharing, which is to inform drivers about the unanticipated demand-supply mismatches that occur in the short-run (Lu et al. 2018).

experiencing an excess supply of drivers and Zone 3 experiencing a shortage of drivers. Initial number of drivers in Zones 1, 2, and 3 is $(1+\gamma)n$, $(2-\gamma)n$, and 0, respectively, where $\gamma \in [0,1]$ captures spatial supply heterogeneity. For example, $\gamma = 0.5$ represents a setting where drivers are equally concentrated in Zones 1 and 2 initially, whereas $\gamma > 0.5$ represents a setting where more drivers are located in Zone 1. Despite the initial supply imbalance across zones, the total supply of drivers is sufficient to cover the total customer demand. We assume that the initial level of supply across the zones is common knowledge among all drivers[3]. Consequently, drivers can infer the realized demand perfectly from the demand–supply mismatch information shared by the platform.

Drivers incur the relocation cost r_1 to move between Zones 1 and 3, and r_2 to move between Zone 2 and 3, where $r_1 > r_2 > 0$. The asymmetry in relocation costs could occur either because the distance between Zones 1 and 3 is greater than that between Zones 2 and 3, or the disutility of moving between Zones 1 and 3 exceeds that of moving between Zones 2 and 3 due to exogenous factors such as the traffic. To focus on drivers' relocation behavior from non-surge to surge zones, we assume that the relocation costs between Zones 1 and 2 are sufficiently high such that drivers would not move between these two zones. Relocation costs are common knowledge among all drivers. An illustration of the three zones and their characteristics is provided in Figure 2.3.

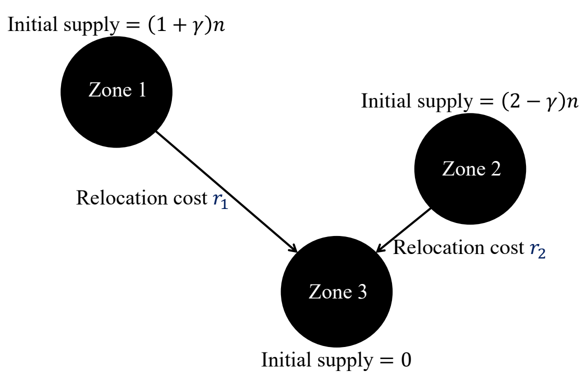


Figure 2.3: Illustration of zones

[3]Drivers commonly access this information from the rider version of a platform's app (Karacaoglu et al. 2018), (https://www.reddit.com/r/uberdrivers/comments/vp19vz/does_everyone_know_how_to_see_where_the_other/) or from other sources such as Google maps.

The platform implements surge pricing; drivers in a surge zone are paid proportionally to the demand *relative* to the available driver supply in that zone (Yan et al. 2020; Castillo et al. 2017; Dholakia 2015; Chen et al. 2015). To focus on the platform's choice of the information-sharing format, we assume that the platform implements a consistent pricing policy across the three information-sharing mechanisms[4], which can be explained as follows. Let s_{jk} denote the number of drivers available to serve customers in Zone j at the end of Stage $k \in \{1, 2\}$. If the demand in Zone j, d_j, is less than or equal to s_{jk}, this implies that Zone j is not surging. In that case, the driver is allocated a customer request with probability d_j/s_{jk} and earns base earning $p > 0$ for completing it. If the driver is not assigned to a customer, the driver earns 0. On the other hand, if $d_j > s_{jk}$, this implies that Zone j is a surge zone. In that case, the driver is allocated a customer request with probability 1 and earns $p \times (d_j/s_{jk})$ for completing the request. Here, the term (d_j/s_{jk}) in the driver's earning captures the *surge multiplier* implemented by the platform, which is proportional to the demand–supply mismatch in the surge zone[5]. By making the demand-supply mismatch a major determinant of the surge multiplier, the platform offers financial incentives for drivers to relocate to the undersupplied area (Lu et al. 2018). Finally, we assume that drivers' relocation costs do not exceed their base earning p, i.e., $p > r_1 > r_2$, such that the spatial information shared to induce relocation is more likely to create value for drivers and the platform.

[4]Surge multiplier is calculated in a consistent manner in all mechanisms. However, the actual value of the surge multiplier depends on the driver supply in a surge zone (as well as demand), which is endogenous to the information-sharing mechanism in implementation.

[5]Explanations to drivers by platforms, including by Uber, DoorDash, Ola and Deliveroo given below, indicate that pricing in a surge zone (and the associated information shared with drivers) is indicative of the underlying demand-supply mismatch: https://www.uber.com/us/en/drive/driver-app/how-surge-works/, https://doordashdriver.blogspot.com/2018/01/doordash-heat-map-really-mean.html, https://blog.olacabs.com/peak-hour-surcharge-the-what-why-and-how-of-it/, https://riders.deliveroo.co.uk/en/news/heatmap. In reality, the surge multiplier may depend on other factors in addition to the level of demand and supply (Chen and Sheldon 2016). We adopt the simplest function of demand and supply as the multiplier that yields tractability in analysis, is continuous, and ensures existence of equilibria. Furthermore, the surge multiplier in a zone is independent of the demand and supply levels in other zones in our model. This is supported by Chen et al. (2015), which report that Uber partitions cities into surge areas and calculates surge multipliers independently for each area.

2.4 Equilibrium Analysis with Rational Drivers

Characterization of Equilibria: We focus on *asymmetric pure strategy equilibria* in our analysis below. Specifically, each driver chooses whether to stay in his initial zone or move to Zone 3 as a best-response to the stay/move decisions of all other drivers. In our setting, each driver's expected net earnings from staying and moving depends only on the total number of drivers choosing to stay in the driver's initial zone and the total number of drivers choosing to move to Zone 3, respectively. The equilibrium conditions identified in Propositions 1-3 below ensure under the respective information-sharing mechanism that neither driver has an incentive to deviate. In addition to summarizing the equilibrium conditions, Propositions 1-3 establish the existence of an equilibrium under the respective information-sharing mechanism.

We first characterize the equilibria with surge information sharing upon the platform revealing the demand-supply mismatch in Zone 3 at the beginning of Stage 1. Since the initial driver supply in Zone 3 is 0 and common knowledge to all drivers, the demand-supply mismatch revealed to drivers is equivalent to the realized Zone 3 demand, $D_3 = d_3$. Hence, proportions of drivers that move from Zones 1 and 2 in equilibrium are denoted as functions of d_3, as $\theta^*_{1s}(d_3)$ and $\theta^*_{2s}(d_3)$, respectively. We focus our attention to $D_3 = d_3 > 0$ as the proof of Proposition 1 establishes that $\theta^*_{1s}(d_3) = \theta^*_{2s}(d_3) = 0$ for $d_3 = 0$.

Proposition 1. *With surge information sharing, there exist thresholds $\underline{r}_s$ and $\overline{r}_s$ such that*

(a) an equilibrium exists in which only some drivers initially in Zone 2 relocate to Zone 3 if and only if $r_1 \geq \overline{r}_s$. In this equilibrium, $\theta^*_{1s}(d_3) = 0$, and the unique $\theta^*_{2s}(d_3) \in (0, 1)$ equals

$$\frac{d_3p + np + (2-\gamma)nr_2 - \sqrt{(d_3p + np + (2-\gamma)nr_2)^2 - 4(2-\gamma)d_3npr_2}}{2(2-\gamma)nr_2}. \tag{2.1}$$

(b) An equilibrium exists in which only some drivers initially in Zone 1 relocate to Zone 3 if and

only if $r_1 \leq \underline{r}_s$. In this equilibrium, $\theta^*_{2s}(d_3) = 0$, and the unique $\theta^*_{1s}(d_3) \in (0,1)$ equals

$$\frac{d_3 p + np + (1+\gamma)nr_1 - \sqrt{(d_3 p + np + (1+\gamma)nr_1)^2 - 4(1+\gamma)d_3 npr_1}}{2(1+\gamma)nr_1}. \tag{2.2}$$

(c) If $\underline{r}_s < r_1 < \overline{r}_s$, a unique equilibrium exists in which a proportion of drivers from both zones relocate to Zone 3. In this equilibrium, $\theta^*_{1s}(d_3) \in (0,1)$ and $\theta^*_{2s}(d_3) \in (0,1)$ uniquely solve

$$\frac{1}{(1+\gamma)(1-\theta^*_{1s})} = \frac{d_3}{n[(1+\gamma)\theta^*_{1s} + (2-\gamma)\theta^*_{2s}]} - \frac{r_1}{p}, \tag{2.3}$$

$$\frac{1}{(2-\gamma)(1-\theta^*_{2s})} = \frac{d_3}{n[(1+\gamma)\theta^*_{1s} + (2-\gamma)\theta^*_{2s}]} - \frac{r_2}{p}. \tag{2.4}$$

(d) $\underline{r}_s > r_2$ if and only if $\gamma > \tilde{\gamma} > 0.5$.

The thresholds $\overline{r}_s$ and $\underline{r}_s$ are defined in the proof of the proposition in Appendix section A.1. According to Proposition 1, three types of equilibria occur with surge information sharing. In the first type of equilibrium (described in part (a)), which occurs when relocating from Zone 1 to Zone 3 is very costly, all drivers in Zone 1 choose to stay in their initial zone, and some of the drivers from only Zone 2 relocate to Zone 3. In the second type of equilibrium (part (c)), which occurs when the cost of relocating from Zone 1 to Zone 3 assumes an intermediate value, the surge zone attracts some drivers from both Zones 1 and 2. The equilibrium conditions (3) and (4) imply that a driver's expected net earnings from staying in its initial zone (in the left-hand-side) is equal to the expected net earnings from moving to Zone 3 (on the right-hand-side) given the actions of all drivers, and hence, neither driver has incentive to deviate. Finally, in the third type of equilibrium (part (b)), which occurs under relatively low costs of relocating from Zone 1 to Zone 3, only some drivers initially in Zone 1 choose to relocate to Zone 3, while Zone 2 drivers stay in their initial zone. Importantly, part (d) implies that the third type of equilibrium emerges as long as the initial driver supply in Zone 1 is higher than in Zone 2, and disappears otherwise (as by definition $r_1 > r_2$). The rationale is that Zone 2 drivers are aware of their relocation cost advantage over Zone 1 drivers, and may be discouraged from moving to Zone 3 if and only if they expect to face stiff competition from Zone 1 drivers, which would occur under a high initial driver supply in Zone 1.

We next characterize the equilibria with full information sharing upon the platform revealing the demand-supply mismatch in all zones at the beginning of Stage 1. Since the initial driver supply in all zones are fixed and common knowledge to all drivers, the demand-supply mismatch information reveals the realized demand in all zones $(D_1, D_2, D_3) = (d_1, d_2, d_3)$ to drivers. Hence, the proportions of drivers that move from Zones 1 and 2 in equilibrium are denoted as functions of d_1, d_2 and d_3 as $\theta^*_{1f}(d_1, d_2, d_3)$ and $\theta^*_{2f}(d_1, d_2, d_3)$, respectively. We focus our attention to $\{d_1, d_2, d_3\} > 0$, while cases with zero demand in one or more zones are relegated to Appendix section A.1 (see Propositions 4-6).

Proposition 2. *With full information sharing, there exist thresholds $\underline{r}_f$ and $\overline{r}_f$ such that*

(a) an equilibrium exists in which only some drivers initially in Zone 2 relocate to Zone 3 if and only if $r_1 \geq \overline{r}_f$. In this equilibrium, $\theta^*_{1f}(d_1, d_2, d_3) = 0$, and the unique $\theta^*_{2f}(d_1, d_2, d_3) \in (0, 1)$ equals

$$\frac{2d_2np + d_3p + (2-\gamma)nr_2 - \sqrt{(2d_2np - d_3p + (2-\gamma)nr_2)^2 + 8d_2d_3np^2}}{2(2-\gamma)nr_2}. \tag{2.5}$$

(b) An equilibrium exists in which only some drivers initially in Zone 1 relocate to Zone 3 if and only if $r_1 \leq \underline{r}_f$. In this equilibrium, $\theta^*_{2f}(d_1, d_2, d_3) = 0$, and the unique $\theta^*_{1f}(d_1, d_2, d_3) \in (0, 1)$ equals

$$\frac{2d_1np + d_3p + (1+\gamma)nr_1 - \sqrt{(2d_1np - d_3p + (1+\gamma)nr_1)^2 + 8d_1d_3np^2}}{2(1+\gamma)nr_1}. \tag{2.6}$$

(c) if $\underline{r}_f < r_1 < \overline{r}_f$, a unique equilibrium exists in which a proportion of drivers from both zones relocate to Zone 3. In this equilibrium, $\theta^*_{1f}(d_1, d_2, d_3) \in (0, 1)$ and $\theta^*_{2f}(d_1, d_2, d_3) \in (0, 1)$

are unique solutions to

$$\frac{2d_1}{n(1+\gamma)(1-\theta^*_{1f})} = \frac{d_3}{n[(1+\gamma)\theta^*_{1f} + (2-\gamma)\theta^*_{2f}]} - \frac{r_1}{p}, \tag{2.7}$$

$$\frac{2d_2}{n(2-\gamma)(1-\theta^*_{2f})} = \frac{d_3}{n[(1+\gamma)\theta^*_{1f} + (2-\gamma)\theta^*_{2f}]} - \frac{r_2}{p}. \tag{2.8}$$

The thresholds $\overline{r}_f$ and $\underline{r}_f$ are defined in the proof of the proposition in Appendix section A.1. Consistent with Proposition 1, Proposition 2 demonstrates three types of equilibria depending on the cost of relocation r_1 from Zone 1: When the relocation cost assumes a value in the two extremes (either very high or low), a proportion of drivers from only one of the zones relocate to Zone 3, whereas the surge zone is able to attract drivers from both zones for intermediate values of the relocation cost. Importantly, the thresholds on the relocation cost identified by Proposition 1 and 2 are different because the thresholds with full information sharing would depend on the local demand conditions in non-surge zones as well as the demand condition in Zone 3, as drivers base their decisions on the demand conditions in all zones.

Finally, Proposition 3 characterizes the equilibria under local information sharing upon the platform revealing the demand-supply mismatch in Zone 3 to only Zone 2 drivers at the beginning of Stage 1. As discussed with surge information sharing, since the initial driver supply in Zone 3 is 0 and common knowledge to all drivers, the revealed demand-supply mismatch in Zone 3 is equivalent to the realized Zone 3 demand, $D_3 = d_3$. Consequently, the proportion of drivers that move from Zone 2 to Zone 3 in equilibrium is a function of d_3 denoted by $\theta^*_{2\ell}(d_3)$. In contrast, drivers initially in Zone 1 do not receive any demand-supply mismatch information from the platform, and hence, the proportion of drivers relocating from Zone 1 to Zone 3 in equilibrium $\theta^*_{1\ell}$ does not vary with d_3. As evident from the proposition below, the types of equilibria observed with local information sharing follow a consistent pattern to those with surge and full information sharing, albeit leading to different thresholds on the relocation cost r_1.

Proposition 3. *With local information sharing, there exist thresholds $\underline{r}_\ell$ and $\overline{r}_\ell$ such that*

(a) an equilibrium exists in which only some drivers initially in Zone 2 relocate to Zone 3 if and

only if $r_1 \geq \overline{r}_\ell$. *In this equilibrium,* $\theta^*_{1\ell} = 0$, *and the unique* $\theta^*_{2\ell}(d_3) \in [0,1)$ *equals*

$$= \frac{d_3 p + np + (2-\gamma)nr_2 - \sqrt{(d_3 p + np + (2-\gamma)nr_2)^2 - 4(2-\gamma)d_3 npr_2}}{2(2-\gamma)nr_2} \tag{2.9}$$

for each $d_3 \in [0, n]$.

(b) An equilibrium exists in which only some drivers initially in Zone 1 relocate to Zone 3 if and only if $r_1 \leq \underline{r}_\ell$. *In this equilibrium,* $\theta^*_{2\ell}(d_3) = 0$ *for all* $d_3 \in [0, n]$, *and the unique* $\theta^*_{1\ell} \in (0,1)$ *equals*

$$\frac{2p}{3p + 2(1+\gamma)r_1 + \sqrt{9p^2 + 4(1+\gamma)r_1\,(p + (1+\gamma)r_1)}}. \tag{2.10}$$

(c) if $\underline{r}_\ell < r_1 < \overline{r}_\ell$, *a unique equilibrium exists in which* $\theta^*_{1\ell} \in (0,1)$ *and* $\theta^*_{2\ell}(d_3) = 0$ *for* $d_3 \in [0, \overline{d}_3]$ *and* $\theta^*_{2\ell}(d_3) \in (0,1)$ *for* $d_3 \in (\overline{d}_3, n]$. *In this equilibrium,* $\overline{d}_3$, $\theta^*_{1\ell}$, *and* $\theta^*_{2\ell}(d_3)$ *uniquely solve*

$$\overline{d}_3 = \frac{(1 + r_2(2-\gamma))(1+\gamma)\theta^*_{1\ell}}{(2-\gamma)}, \tag{2.11}$$

$$\frac{1}{(2-\gamma)(1-\theta^*_{2\ell}(d_3))} = \frac{d_3}{n[(1+\gamma)\theta^*_{1\ell} + (2-\gamma)\theta^*_{2\ell}(d_3)]} - \frac{r_2}{p} \text{ for each } d_3 > \overline{d}_3, \tag{2.12}$$

$$\frac{1}{(1+\gamma)(1-\theta^*_{1\ell})} = E\left[\frac{d_3}{n[(1+\gamma)\theta^*_{1\ell} + (2-\gamma)\theta^*_{2\ell}(d_3)]}\right] - \frac{r_1}{p}. \tag{2.13}$$

The thresholds $\overline{r}_\ell$ and $\underline{r}_\ell$ are defined in the proof of the proposition in Appendix section A.1.

In comparing the three information-sharing mechanisms, we utilize *expected matching efficiency* as the primary performance metric, which is characterized next. This metric is motivated by practice, wherein the average portion of ride requests completed is a key metric tracked by the top management of platforms such as Uber (Bradshaw and Lee 2022).

Matching Efficiency: Based on prior literature (Banerjee et al. 2022; Özkan and Ward 2020; Jiang et al. 2021), we define expected matching efficiency as the expected proportion of customers served across the three zones in Stage 2,

$$E\left[\frac{\min\{d_1,(1+\gamma)n(1-\theta_{1m_i})\}}{d_1+d_2+d_3}\right]+E\left[\frac{\min\{d_2,(2-\gamma)n(1-\theta_{2m_i})\}}{d_1+d_2+d_3}\right]+ \\ E\left[\frac{\min\{d_3,(1+\gamma)n\theta_{1m_i}+(2-\gamma)n\theta_{2m_i}\}}{d_1+d_2+d_3}\right], \quad (2.14)$$

where $m_i \in \{s, f, \ell\}$ refers to the information-sharing mechanism, and θ_{1m_i} and θ_{2m_i} are the proportions of drivers moving from Zone 1 and Zone 2 under mechanism m_i, respectively, according to Propositions 1-3. The expectation in (Equation 2.14) is taken over the demand distributions of d_1, d_2, and d_3. In examining the matching efficiency below, we consider Stage 2 exclusively because the impact of drivers' decisions on matching outcomes is fully reflected at that stage[6].

Importantly, equilibrium conditions in Proposition 1-3 depend only on the following key parameters of the model, which are all between 0 and 1: relocation costs relative to the driver's base earning p, demand levels relative to the maximum possible demand, and the initial balance of drivers in Zones 1 and 2 captured in the parameter γ. This allows us to evaluate the matching efficiency under all parameter conditions for each information-sharing mechanism numerically, and make comparisons across mechanisms. Figure 2.4 summarizes how relocation costs affect the ordering between the three information mechanisms in terms of expected matching efficiency.

Observation 1. *Comparisons of information-sharing mechanisms in terms of expected matching efficiency are qualitatively similar to those in Figure 2.4a for $\gamma \geq \underline{\gamma}$, and to those in Figure 2.4b for $\gamma < \underline{\gamma}$. For $\gamma \in [\overline{\gamma}, 1]$ (where $\overline{\gamma} > \underline{\gamma}$), the region wherein surge and local information sharing are equivalent disappears, as shown in Figure 2.4c.*

To explain the intuition behind Figure 2.4a, we first consider the comparison of surge and full information sharing. With either mechanism, the platform is able to achieve a high matching efficiency in expectation in non-surge zones due to the abundant initial supply in these zones. Therefore, in our discussion below, we focus on how full and surge information sharing affect

[6]Figure A.1 in Appendix subsection A.2.1 shows that the main insights on the comparison of expected matching efficiency across different information-sharing mechanisms continue to hold when both stages are considered.

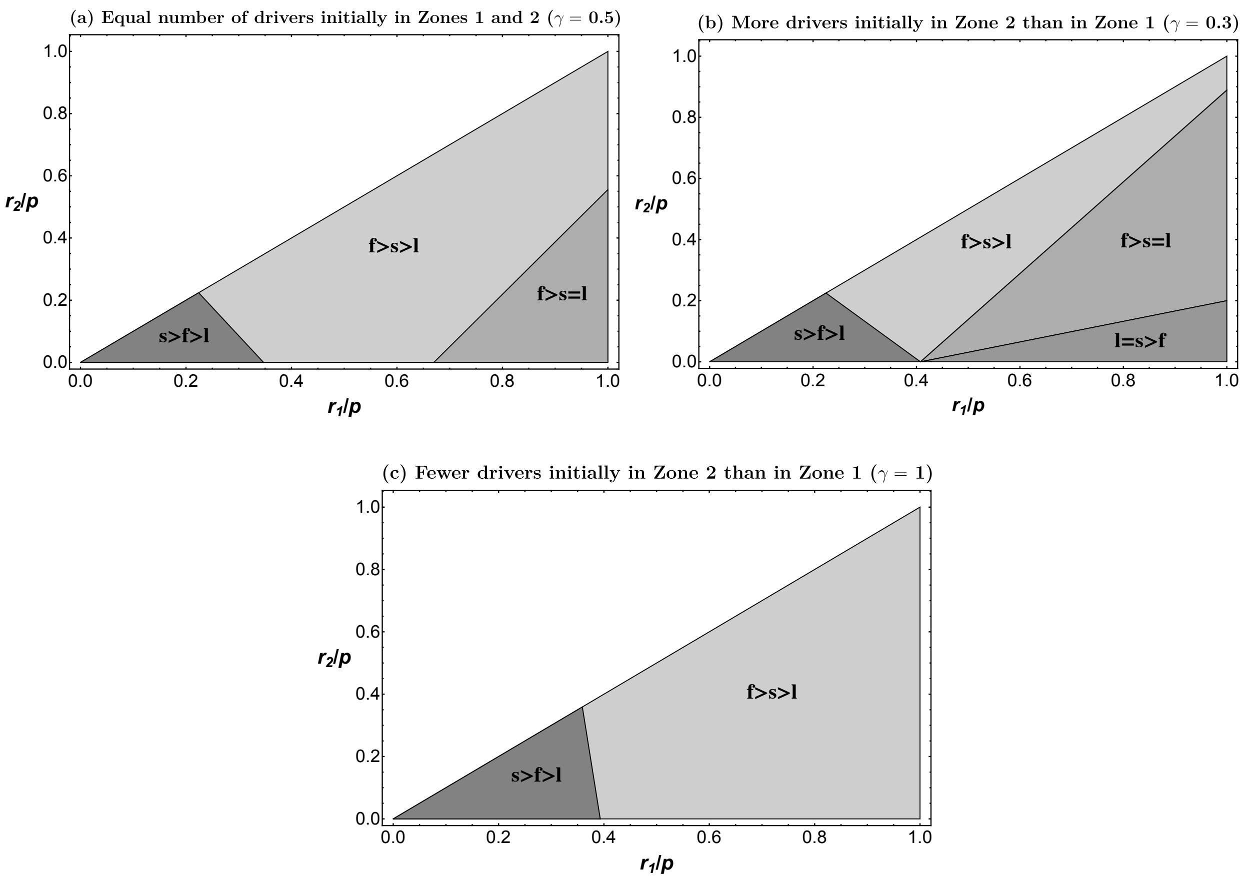


Figure 2.4: Comparison of expected matching efficiency under full, surge, and local information mechanisms.

the matching efficiency in Zone 3. Suppose that relocation costs are low (dark gray region). With surge information sharing, moving to Zone 3 is attractive for even modest surge conditions because of the greater earning opportunities available to drivers in Zone 3 and low relocation costs. As a result, surge information sharing is able to attract many drivers to Zone 3, sufficient to cover the surge demand in that zone for most demand scenarios.[7] With full information sharing, drivers learn not only about the surge conditions in Zone 3, but also the demand–supply mismatch in their own zone. Then, facing the same level of surge, more drivers move to Zone 3 in equilibrium with full information sharing (than with surge information sharing) upon finding out about low demand in non-surge zones, and fewer drivers move to Zone 3 in equilibrium with full information sharing (than with surge) upon learning about high demand in non-surge zones. In the former case, full information sharing provides limited (if any) improvement in matching efficiency over surge information sharing because surge information sharing is already able to achieve a high matching efficiency in Zone 3, whereas in the latter case, full information sharing has the disadvantage of serving fewer customers in Zone 3.[8] Therefore, the overall matching efficiency is lower in expectation with full information sharing than with surge information sharing.

As relocation costs increase, drivers are deterred from moving, which reduces the matching efficiency in Zone 3 achievable with either mechanism. Then, by mobilizing drivers towards Zone 3 particularly under low demand conditions in non-surge zones, full information sharing helps to improve the matching efficiency under such demand scenarios and in expectation over surge information sharing.

Now consider the comparison of surge and local information sharing in Figure 2.4a. When costs of relocating from the two non-surge zones are not too different and a considerable supply of drivers is initially farther away, surge information sharing leads to higher matching efficiency than local. The rationale is that publicly revealing the surge allows the platform to tailor driver supply to demand conditions in Zone 3: Driver supply attracted from both zones is commensurate with

[7]Proposition 7 in Appendix section A.1 theoretically establishes for the limiting case with $\{r_1, r_2\} \to 0$ that surge information sharing leads to 100% matching efficiency in all zones for all demand scenarios.

[8]Proposition 7 in Appendix section A.1 shows in the limiting case with $\{r_1, r_2\} \to 0$ that with full information sharing, demand in Zone 3 may not be satisfied fully.

the level of surge demand. In contrast, with local information sharing, drivers in Zone 1 remain uncertain about the level of surge and base their decision on the average demand conditions. As a result, fewer drivers relocate than needed to cover demand in Zone 3 when the surge demand is relatively high, reducing the matching efficiency in Zone 3, and more drivers than needed relocate to Zone 3 otherwise, potentially reducing the matching efficiency in Zone 1. As the relocation cost r_1 further increases relative to r_2, it follows from Propositions 1a and 3a that all drivers in Zone 1 choose to stay in their initial zone with surge or local information sharing. Then, both mechanisms attract the same level of driver supply from the nearby zone and yield the same matching efficiency.

Figure 2.4a demonstrates that full information sharing yields greater matching efficiency than local when the initial supply of drivers in the distant non-surge zone is not low ($\gamma \geq \underline{\gamma}$). With local information sharing, drivers in Zone 2 have better information on the surge conditions than those in Zone 1. Drivers in Zone 1 anticipate that many drivers from Zone 2 will relocate under highly favorable surge conditions, which reduces Zone 1 drivers' own incentive to move, and under other surge conditions, moving will not be worth the relocation cost. Hence, in expectation, drivers in Zone 1 are not highly incentivized to move with local information sharing. The platform then relies predominantly on the supply of drivers in Zone 2 to cover demand in Zones 2 and 3, which falls short in the region $\gamma \geq \underline{\gamma}$.

The comparison of information-sharing mechanisms in Figure 2.4b (representative of $\gamma < \underline{\gamma}$) is highly consistent with Figure 2.4a. The only exception is a new region on the lower right corner, wherein surge information sharing dominates full information. In this region, high relocation costs and the large supply of drivers available nearby the surge zone deter Zone 1 drivers from moving to Zone 3 regardless of the information-sharing mechanism. Then, the dynamics of Zone 2 drivers' relocation decisions are similar to the dark gray region in Figure 2.4a explained above: Facing low relocation costs, surge information sharing is able to attract many drivers from Zone 2 to meet the surge demand for most demand scenarios, whereas fewer drivers end up moving with full information sharing if the demand in Zone 2 is revealed to be high. That ends up reducing the overall matching efficiency in expectation with full information sharing.

Overall, these comparisons reveal that privately targeting drivers through local information sharing is strictly dominated in the region $\gamma \geq \underline{\gamma}$ by at least one of the public information-sharing mechanisms where all drivers observe the same information, and is redundant otherwise because another information-sharing mechanism performs at least as well. Therefore, private information sharing based on proximity only (as advertised by some platforms (Helling 2023)) without factoring in the supply availability or competitive dynamics can hurt the efficiency of a platform if drivers are fully rational.

Observation 2. *Local information sharing is strictly dominated in terms of matching efficiency by full or surge information sharing for* $\gamma \geq \underline{\gamma}$.

2.5 Experimental Design

The primary goal of our experiments is to examine how the format of demand–supply mismatch information sharing influences the platform's matching efficiency. Consistent with prevailing practice, we choose an experimental setting where the platform's adoption of surge information sharing is supported by standard theory to give theory its best shot: We consider a setting where surge is predicted to achieve greater overall matching efficiency than full and local information sharing.

We used a between-subject design where each participant assumed the role of a driver on an on-demand service platform and completed one of three different treatments—each corresponding to an information-sharing format defined above (full, surge, or local). Participants, who were recruited from the student body at a large public university in the United States and compensated monetarily according to their performance, made stay/move decisions over multiple independent periods. Participants reviewed the instructions and completed a comprehension quiz before they joined the experiment.

Each participant was assigned to either Zone 1 or Zone 2 at the beginning of the experiment and started each period in the same zone throughout the experiment. Each period consisted of two stages. At the beginning of Stage 1, demand values were drawn randomly for each of the three zones according to the demand distributions described in section 2.3. Then, depending on the treatment, each participant received either some or no information about the initial demand–supply mismatch in different zones. For example, all participants were able to observe the initial demand–supply mismatch for all zones in the full information treatment, whereas in the local information treatment, only the participants assigned to Zone 2 were able to observe the demand–supply mismatch in Zone 3. Table 2.1 illustrates the information available to each participant in each treatment. Demand–supply mismatch is calculated as demand minus the number of drivers in a particular zone. Then in Stage 1, participants simultaneously decided whether to stay in their respective zones or move to Zone 3. Participants choosing to stay spent both stages in their zone, whereas participants choosing to move spent Stage 1 relocating, and Stage 2 in Zone 3. In their zone of presence in any stage, a participant was allocated a customer for sure if demand exceeded supply, and earned $p * (demand/supply)$, whereas if supply exceeded demand, they were allocated a customer with probability $(demand/supply)$ in that zone, earning p, and were not allocated a customer with probability $1 - (demand/supply)$, and earned 0. Participants deciding to move were not considered for demand allocation in Stage 1. At the end of Stage 1, participants were provided with updated demand–supply mismatch information (if applicable) based on the decisions of all drivers. Participants were also informed whether a customer was assigned to them. Stage 2 proceeded in a similar manner except that participants did not make relocation decisions in this stage. The feedback information shown at the end of each period involved a summary of the initial mismatch information shared and updated mismatch information from Stages 1 and 2 for each participant, whether a customer was assigned to the participant in each of the stages, the participant's earnings from each stage and for the entire period, and the cumulative earnings. The information structure for Stage 2 and illustrations of the experimental interface are provided in Table A.7 and Figure A.3-Figure A.6, respectively, in Appendix section A.3.

To incorporate real effort, each participant went through a task phase in each stage lasting for about a minute, wherein the participant was presented with a random traffic sign and was asked to move the slider to an appropriate action. To ensure that participants applied effort, credits were deducted for each traffic sign that a participant gave an incorrect or no response to.

The experiments were conducted in the Spring of 2022. In total, 98 participants were recruited; there were 33 in the surge, 32 in the full, and 33 students in the local treatment[9]. Due to the social distancing guidelines during the COVID-19 pandemic, experiments were conducted online. The experimental interface was developed using SoPHIE (Hendriks 2012). During the experiment, participants were asked to simultaneously join a video conference on Zoom with their web cameras turned on for monitoring. At the beginning of the experiment, we reviewed the details of the experimental task and answered participants' questions. Participants then played through 5 trial periods for no monetary incentive, after which they proceeded to the main experiment. Participants made decisions over 40 periods and each treatment took about 90 minutes to complete. At the end of the experiment, participants were asked whether they had any practical experience of working as a service provider for a gig economy platform (e.g., Uber, Lyft, DoorDash, Grubhub etc.). Overall, 11 out 98 participants (3 in full, 5 in surge, and 3 in the local treatment) stated that they had such prior experience. Participants were paid \$5 as a show-up fee. The average total earnings in the full, surge, and local information treatments were \$30.45, \$29.65, and \$29.79, respectively.

In all experiments, we set the parameter values as follows: The maximum customer demand in each zone was $n = 11$ and the total number of drivers was $3n = 33$. The demand in each zone was uniformly distributed between 0 and 11. The spatial supply heterogeneity parameter was set to be $\gamma = 1$, meaning that 22 drivers were initially assigned to Zone 1 and 11 drivers to Zone 2. Relocation costs for drivers in Zones 1 and 2 were set to be $r_1 = 2.5$ and $r_2 = 2$, respectively. Drivers' base earning for a ride was $p = 10$. We used the same sequence of demand values across all treatments.

Our parameter region represents a scenario with $\gamma \geq \underline{\gamma}$ and low relocation costs described in section 2.4, wherein highest expected matching efficiency should be achieved with surge information sharing, followed by full and local information sharing, respectively. Thus, we implement

[9]Number of drivers in each experiment was set to be 33. In the event that there were fewer than 33 human participants, the remaining drivers were computerized to make random decisions. Participants were informed about the number of computerized drivers in the experiments (only 1 in the full treatment), and hence, knew that the vast majority of participants were human. They were not informed about the computerized drivers' strategies or their initial zones.

a setting where the platform's decision to adopt surge information sharing is supported by standard theory. As the total supply is always at least as much as the total demand in our model, the matching efficiency performance is primarily driven by the platform's ability to match supply and demand in the surge zone. Consequently, expected matching efficiency in the surge zone follows the same ranking in our parameter region. Furthermore, for each information-sharing mechanism, our theoretical predictions on the overall matching efficiency as well as the matching efficiency in surge and non-surge zones serve as benchmarks to experimental observations. These theory benchmarks are displayed in Table 2.2. Our theoretical predictions are stated as formal hypotheses below, which we test experimentally and report in the next section.

Hypothesis 1. *Under each information-sharing mechanism, the overall matching efficiency, and matching efficiency in surge and non-surge zones are equal to what theory predicts (Table 2.2).*

Hypothesis 2. *(a) The overall matching efficiency is highest with surge information sharing, followed by full and local information sharing, respectively.*

(b) The matching efficiency in the surge zone is highest with surge information sharing, followed by full and local information sharing, respectively.

2.6 Experimental Results

In this section, we examine the experimental performance of the three information-sharing mechanisms and compare them to theory predictions. We also identify the sources of the deviations through analyzing drivers' relocation behavior. In the analysis below, theoretically predicted matching efficiency is used interchangeably with expected matching efficiency studied in section 2.4.

2.6.1 Matching Efficiency

Table 2.2 provides the theoretically predicted vs. experimental matching efficiencies in the surge zone (Zone 3), non-surge zones (Zones 1 and 2 combined), and across all zones. The theoretically predicted matching efficiency is calculated per period given the demand conditions and then averaged across periods. In calculating experimental matching efficiency, we focus on human participants' decisions, and exclude computerized drivers' decisions from the analysis. Doing so enables us to study the consequences of human drivers' decisions on matching efficiency and make fair comparisons between theoretical and observed outcomes.[10]

Table 2.2: Matching efficiency in Stage 2 in theory vs. experiments

	Surge Zone		**Non-Surge Zones**		**Overall**	
Treatment	**Theory**	**Experiment**	**Theory**	**Experiment**	**Theory**	**Experiment**
full	93.43%	98.81%	100%	100%	98.02%	99.37%
surge	98.64%	100%	100%	97.02%	99.43%	97.94%
local	85.83%	96.19%	99.82%	98.33%	93.49%	97.41%

Table 2.2 demonstrates that directionally, the platform achieves *lower* overall matching efficiency than predicted in the surge treatment, while it achieves *higher* overall efficiency than predicted under the full and local treatments. Considering surge and non-surge zones separately provides a clearer picture: In the surge zone, the platform achieves greater matching efficiency than predicted under all three treatments, although this is especially pronounced with full and local information sharing. In the non-surge zones, however, the platform experiences some reduction in matching efficiency relative to theory with surge and local information sharing, with the magnitude of difference being relatively larger in case of the surge treatment. These directional observations on efficiency are further supported by the density plots in Figure A.2 in Appendix subsection A.2.2, which illustrate the ratio of experimental to theoretically predicted matching efficiency for each set of demand instances tested in the experiment, thereby helping to compare theory and experiments in greater detail.

To test formally how the matching efficiency compares in theory versus experiments, we use a

[10]For this purpose, we calculate the supply of drivers that move from Zones 1 and 2 by taking the proportion of human drivers who chose to move from Zones 1 and 2, and then scaling them by multiplying with the initial number of drivers in each zone. We then calculate the experimental matching efficiency for each period given the specific demand condition tested in that period and report the average across periods in Table 2.2.

regression model, as shown below:

$$\Delta_{kt}^{j} = \lambda_0 + \lambda_1 \times TRS_{kt} + \lambda_2 \times TRL_{kt} + \lambda_3 \times t + \lambda_4 \times (TRS_{kt} \times t) + \lambda_5 \times (TRL_{kt} \times t) + \epsilon_{kt}. \tag{2.15}$$

In this equation, the dependent variable is the difference between experimental and theoretically predicted matching efficiency in treatment k in period t of the experiment, and j corresponds to the zone in question (i.e., $\{s, ns, o\}$ corresponding to surge zone, non-surge zones (Zones 1 & 2), and overall). TRS_{kt} and TRL_{kt} are the dummy variables for surge and local treatments, respectively. We control for the effect of period using the continuous variable t, which ranges from 1 to 40. ϵ_{kt} is the error term, which is assumed to be normally distributed with zero mean and a positive standard deviation. We provide the regression estimates in Table 2.3 (models (1)-(3)).

Since the effect of surge and local treatments and the time trend are represented by separate terms in our regression model, a direct comparison of the matching efficiency with theory is not immediately available from the regression analysis. Therefore, we use linear hypothesis testing (Freund et al. 2006) to formally test theory predictions. Specifically, for each treatment, we first calculate the estimated gap in matching efficiency between experiment and theory averaged over period and then compare it to 0. Table A.1 in Appendix subsection A.2.3 shows our linear hypotheses and Table 2.4 reports the results.

We find that the overall experimental matching efficiency is marginally lower than in theory under surge ($p < 0.1$), while being marginally greater than in theory under full ($p < 0.1$) and significantly greater than in theory under local information sharing ($p < 0.01$). Therefore, *the platform serves fewer customers than predicted with surge information sharing, whereas it serves more customers than predicted with full and local information sharing* in our experiments. Furthermore, the loss of efficiency in the surge treatment appears to stem from matching efficiency in the non-surge zones being lower than predicted ($p < 0.01$), whereas the efficiency improvement with full and local treatments appears to stem from matching efficiency in the surge zone being greater than predicted ($p < 0.05$ and $p < 0.01$, respectively). Therefore, Hypothesis 1 is not supported.

Table 2.3: Regression analysis of experimental matching efficiency

	ΔMatching Efficiency (Exp-Theory)			**Matching Efficiency**		
	Δ^s	Δ^{ns}	Δ^o	m^s	m^{ns}	m^o
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.002	−0.000	0.002	0.987**	1.000**	0.996**
	(0.046)	(0.013)	(0.021)	(0.022)	(0.014)	(0.014)
TRS	−0.000	−0.050**	−0.037	0.013	−0.050*	−0.032
	(0.064)	(0.018)	(0.030)	(0.031)	(0.020)	(0.019)
TRL	0.110†	−0.017	0.035	−0.030	−0.016	−0.021
	(0.064)	(0.018)	(0.030)	(0.031)	(0.020)	(0.019)
t	0.003	0.000	0.001	0.0001	0.000	−0.0001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$TRS \times t$	−0.002	0.001	0.0004	−0.0001	0.001	0.001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$TRL \times t$	−0.003	0.0001	−0.0005	0.0002	−0.00002	0.0001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Number of observations in all models is 120. †p<0.1; *p<0.05; **p<0.01.

Table 2.4: Experimental vs. theoretically predicted matching efficiency: Linear hypothesis testing results

Treatment	**Surge Zone**	**Non-Surge Zones**	**Overall**
full	**Higher** $p =$**0.010***	n.s. $p =1$	**Higher** $p =$**0.098**†
surge	n.s. $p =0.553$	**Lower** $p =$**0.000****	**Lower** $p =$**0.068**†
local	**Higher** $p =$**0.000****	**Lower** $p =$**0.009****	**Higher** $p =$**0.000****

†p<0.1; *p<0.05; **p<0.01. Non-significant results are denoted by *n.s* and reported with p-values from two-sided tests.

These findings may indicate that all three treatments mobilize more drivers than predicted, but at varying degrees depending on the drivers' zone of origin: For example, if the surge treatment mobilizes more Zone 2 drivers than in theory, this may contribute to a reduction in the matching efficiency in Zone 2, as the initial driver supply is lower in that zone. In contrast, if full and local treatments mobilize more Zone 1 drivers than in theory, they may achieve greater matching efficiency in the surge zone without sacrificing the matching efficiency in non-surge zones as much. We explore these conjectures on drivers' relocation behavior in detail in subsection 2.6.2.

To compare matching efficiency across treatments, we implemented a regression model similar to that in (Equation 2.15), as shown below:

$$m^{j}_{kt} = \beta_0 + \beta_1 \times TRS_{kt} + \beta_2 \times TRL_{kt} + \beta_3 \times t + \beta_4 \times (TRS_{kt} \times t) + \beta_5 \times (TRL_{kt} \times t) + \epsilon_{kt}. \tag{2.16}$$

The dependent variable m^{j}_{kt} is the experimental matching efficiency in treatment k, period t, and j corresponds to the zone in question. All other variables are as defined in (Equation 2.15). Our linear hypotheses are shown in Table A.2 in Appendix subsection A.2.3, and the regression results are summarized in Table 2.3 (models (4)-(6)).

After controlling for the direct effect of time and its interaction with different treatments, we observe that *surge information sharing does not provide a better matching performance compared to full or local information sharing*. In fact, the matching performance of full information sharing is marginally *higher* than that of surge (*p*-value $= 0.063$), while the performance of local information sharing is *comparable* (two-sided *p*-value $= 0.613$). Therefore, Hypothesis 2(a) is not supported. Considering the two alternative mechanisms, full information sharing achieves *greater* overall matching efficiency compared to local information sharing in our experiments (*p*-value $= 0.021$).

Conducting a similar analysis for the matching efficiency of the surge zone only, we find evidence for surge information sharing outperforming local information sharing (*p*-value $= 0.007$), but not full information sharing (two-sided *p*-value for surge vs. full treatment is $= 0.442$). Therefore, Hypothesis 2(b) is only partially supported. Furthermore, both full and local treatments tend to outperform the surge treatment in matching performance in the non-surge zones (*p*-values for full vs. surge and local vs. surge are 0.001 and 0.082, respectively). This leads us to conclude that the loss of matching efficiency in the non-surge zones provides a rationale for why surge information sharing does not dominate other mechanisms in the overall matching efficiency.

2.6.2 Drivers' Relocation Decisions

To facilitate our understanding of the matching efficiency results in subsection 2.6.1, we analyze human participants' relocation decisions in detail. Figure 2.5 shows how the number of drivers

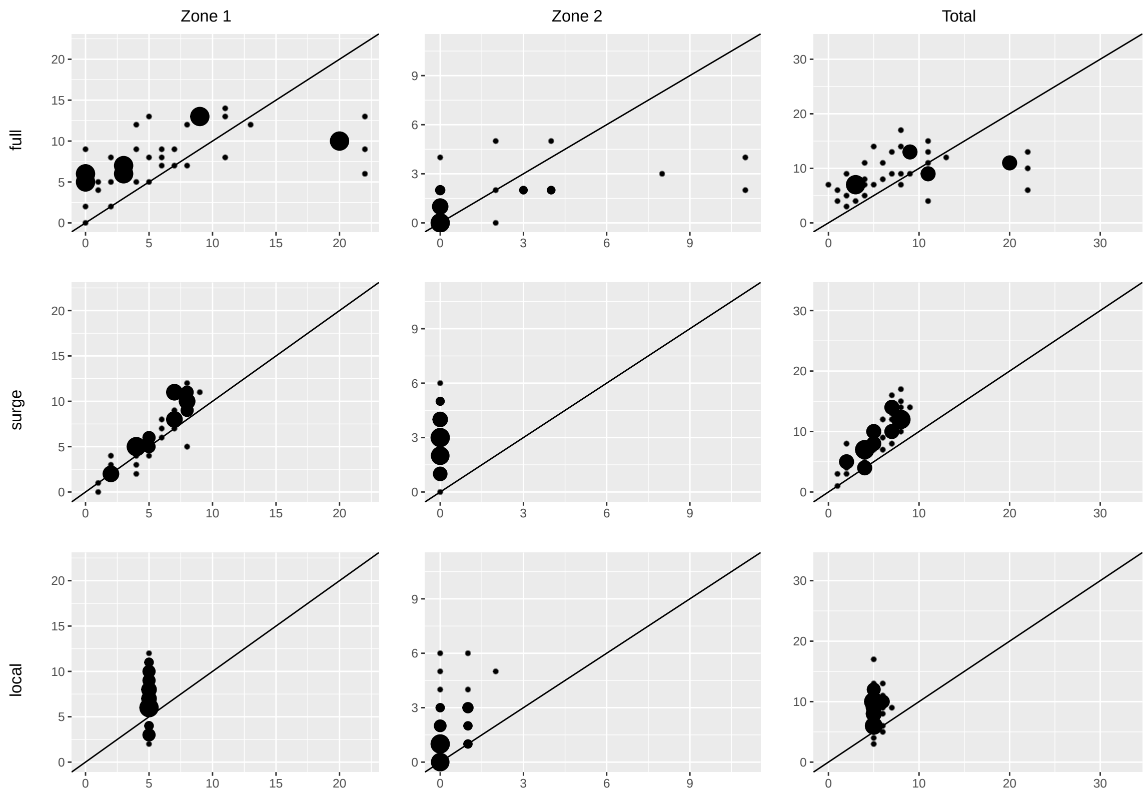


Figure 2.5: Experimental and theoretically predicted number of drivers relocating from Zone 1, Zone 2, and the two zones combined, on vertical and horizontal axis, respectively.

Note: The size of the dot indicates the frequency of a particular observation.

choosing to relocate from Zone 1, Zone 2, and in total compares to the theory predictions across all periods in the experiments. The first row in Figure 2.5 suggests that with full information sharing, fewer drivers tend to relocate than theory when there is a bigger gap in demand–supply mismatch across surge and non-surge zones (which corresponds to the right half of the figures), and more drivers relocate than theory otherwise. In contrast, the second row of Figure 2.5 corresponding to surge treatment suggests that drivers initially assigned to Zone 2 tend to relocate more frequently than theory, which appears to result in higher total traffic from non-surge to surge than theory as well. With local information sharing (third row in Figure 2.5), we find visual evidence for more drivers leaving Zones 1 and 2 compared to theory, which results in higher total traffic than predicted.

To formally test drivers' relocation decisions against theory, we use a regression model that controls for time and individual specific effects. Interpreting the proportion of relocating drivers from Zone j given the demand conditions in period t, θ^j_{it}, as the theoretically predicted probability of moving for a driver, the dependent variable $(c^j_{it} - \theta^j_{it})$ captures the difference between the observed choice c^j_{it} of driver i (equal to 1 if the driver i moves, and 0 otherwise) and theory prediction in period t. We use the following regression specification:

$$\begin{aligned}(c^j_{it} - \theta^j_{it}) = \alpha_0 + \alpha_1 \times TRS_{it} + \alpha_2 \times TRL_{it} + \alpha_3 \times t + \alpha_4 \times (t \times TRS_{it}) \\ + \alpha_5 \times (t \times TRL_{it}) + \nu_i + \epsilon_{it}.\end{aligned} \tag{2.17}$$

Here, j corresponds to the initial zone in question for drivers (i.e., $\{1, 2, o\}$ corresponding to Zone 1, Zone 2, and overall). The term ν_i captures the individual-specific random effect. ϵ_{it} is the error term, which is assumed to be normally distributed with zero mean and a positive standard deviation. As in subsection 2.6.1, we use linear hypothesis tests to examine the direction of the dependent variable in an average period in the experiment. Table A.3 in Appendix subsection A.2.3 shows our linear hypotheses, Table 2.5 shows the regression results, and Table 2.6 shows the linear hypothesis results.

In the full treatment, we find that while Zone 1 drivers display a marginally greater frequency of relocation than in theory ($p = 0.093$), overall, drivers' relocation decisions do not significantly deviate from theory ($p = 0.303$). In the surge treatment, while Zone 1 drivers' relocation behavior remains consistent with theory ($p = 0.327$), drivers in Zone 2 choose to move more frequently than in theory ($p < 0.01$). This translates into greater overall movement than predicted ($p < 0.01$). In the local treatment, drivers in both zones choose to move more frequently than in theory ($p < 0.05$ and $p < 0.01$, respectively,), leading to greater overall movement ($p < 0.01$).

These observations help us to reconcile the deviations in experimental matching efficiency from theory described in subsection 2.6.1. With full information sharing, although drivers' overall relocation patterns are consistent with predictions, the marginal increase in Zone 1 drivers' relocation frequency from theory can contribute to a boost in the overall matching efficiency: Since Zone 1 has very high supply relative to demand, even a slight increase in drivers' tendency to move out of

Table 2.5: Observed vs. predicted probability of moving: Regression models with random-effects for individuals.

	Dependent variable: (c^j - θ^j)		
	Zone 1 Drivers	Zone 2 Drivers	All Drivers pooled
	(1)	(2)	(3)
Constant	0.038 (0.053)	0.011 (0.050)	0.029 (0.040)
TRS	0.040 (0.075)	0.290** (0.071)	0.124* (0.057)
TRL	0.064 (0.075)	0.216** (0.071)	0.115* (0.057)
t	0.001 (0.001)	-0.001 (0.002)	0.000 (0.001)
$TRS \times t$	-0.003 (0.002)	-0.002 (0.002)	-0.002† (0.001)
$TRL \times t$	-0.002 (0.002)	-0.004† (0.002)	-0.003† (0.001)
Observations	2600	1320	3920

Standard errors in parentheses. †p<0.1; *p<0.05; **p<0.01.

Table 2.6: Observed vs. predicted probability of moving: Linear hypothesis testing results.

Treatment	**Zone 1 Drivers**	**Zone 2 Drivers**	**Overall**
full	**Higher** p =**0.093**†	n.s. p =0.762	n.s p =0.303
surge	n.s. p =0.327	**Higher** p =**0.000****	**Higher** p =**0.001****
local	**Higher** p =**0.0373***	**Higher** p =**0.001****	**Higher** p =**0.003****

†p<0.1; *p<0.05; **p<0.01. Non-significant results are denoted by *n.s* and reported with p-values from two-sided tests.

that zone can help the platform to match more customers in the surge zone, without compromising the matching performance in Zone 1 as much.

As discussed in section 2.1, most platforms have employed surge information sharing as their primary mode of sharing information. Our experimental results show that *human drivers are more likely to relocate than in an equilibrium with rational drivers under surge information sharing*, which is consistent with the "flocking" problem observed in practice. Note however that despite helping to increase the matching efficiency in the surge zone directionally, this higher frequency of relocation does not compensate for the loss of efficiency in the non-surge zones and is therefore redundant, while in reality it will be undesirable for contributing to traffic congestion.

An over-movement tendency persists with local information sharing, wherein *human drivers from both non-surge zones are more likely to relocate than in theory*. Although this tendency creates a loss of efficiency in non-surge zones and particularly in Zone 2, the platform is able to overcome that by matching the surge demand more effectively through mobilizing Zone 1 drivers located farther from the surge zone. Consequently, the platform is able to achieve a greater overall matching efficiency than predicted.

To examine whether participants' prior experience working as a service provider (or not) influence their relocation decisions in the experiments, we replicate our analysis in Table 2.5 with an additional variable capturing prior practical experience. Results reported in Table A.6 in Appendix subsection A.2.6 show that participants' deviations from theory are not significantly affected by their prior experience.

Table 2.7: Effect of information on drivers' decisions. Logistic regression models with random-effects for individuals.

	Dependent variable: $logit(Pr(c_{it}^{j}=1))$					
	Zone 1 full	Zone 2 full	Zone 1 surge	Zone 2 surge	Zone 1 local	Zone 2 local
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-1.487^{**}	-2.745^{**}	-3.344^{**}	-1.628^{**}	$-0.599^{\dagger}$	-2.396^{**}
	(0.356)	(0.739)	(0.509)	(0.512)	(0.341)	(0.448)
d_1	-0.069^{**}	0.158^{**}				
	(0.024)	(0.052)				
d_2	0.066^{**}	-0.233^{**}				
	(0.024)	(0.057)				
d_3	0.151^{**}	0.200^{**}	0.404^{**}	0.101^{*}	-0.042	0.235^{**}
	(0.031)	(0.071)	(0.042)	(0.048)	(0.031)	(0.059)
t	0.0002	-0.042^{**}	$-0.016^{\dagger}$	-0.017	-0.007	-0.037^{**}
	(0.007)	(0.015)	(0.008)	(0.011)	(0.007)	(0.012)
Observations	840	440	880	440	880	440

Standard errors in parentheses. $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$.

To gain further insight into human drivers' decisions, we consider how the information revealed by the platform influences their decisions. Using logistic regression models, we regress drivers' stay/move choices against the demand information available to them, time, and random-effects for individuals. We conduct this analysis for each zone and treatment separately because the information available can be different across treatments and zones. Results are shown in Table 2.7. All notation is as defined previously.

Models (1) and (2) in Table 2.7 demonstrate that in the full treatment, drivers utilize all pieces of the shared demand information in their decision making and in a consistent manner with theory. Drivers were more likely to move when the demand surge was higher and less likely to move when the demand in their own zone was higher. Interestingly, drivers were sensitive to demand in the other non-surge zone: They moved more frequently when the demand in the other non-surge zone was higher, which is indicative of their *strategic concerns* about the behavior of drivers in the other non-surge zone.

Models (3), (4), and (6) in Table 2.7 demonstrate under both surge and local treatments that, as expected, drivers informed about the surge opportunity were more likely to move when the level of surge was higher. In contrast, Zone 1 drivers were not sensitive to the level of demand surge in the local treatment, thereby confirming that there was no leakage of demand information in our experiment. The negative time-effect in models (2), (3), and (6) suggests that the surge zone was not as attractive to some drivers over time as they gained more experience, which aligns with the sentiment among many drivers in practice (Ong et al. 2021). Moreover, this tendency exhibited by Zone 1 drivers in the surge treatment and Zone 2 drivers in the local treatment can be due to the greater competition these drivers face from drivers relocating from the other non-surge zone.

In Table A.5 in Appendix subsection A.2.5, we show that the main insights from Table 2.7 discussed above continue to hold after controlling for drivers' decisions and earnings in the previous experimental period through lagged variables. Additionally, this analysis supports our intuition that a driver is more likely to choose the same decision as in the previous period after achieving high earnings from that decision.

2.7 Behavioral Model

Experimental results in section 2.6 suggest that participants' decisions deviate from the rational equilibrium prediction. In the surge and local treatments, we observe a greater tendency to relocate by drivers initially nearby the surge zone. We also observe greater movement of drivers located farther from the surge zone in the local treatment. Under the full treatment, drivers' relocation decisions tend to be consistent with theory overall, while there is some evidence that drivers farther from the surge zone display a marginally greater tendency to relocate.

To explain these observations behaviorally, we first consider *regret aversion* as a possible explanation. Regret aversion suggests that drivers make decisions to reduce the regret they would experience once the chosen and foregone alternatives are resolved. To explore its role in our experiments, we considered an expected utility model, which includes the drivers' earnings resulting from stay/move decisions as well as their anticipated regret. Here, we assume that drivers do not experience regret when the foregone option is not revealed explicitly (Zeelenberg 1999), but when it is, the expected disutility from regret is equivalent to foregone surplus multiplied by the regret coefficient and the probability of experiencing that regret (Özer and Zheng 2016). For example, this implies that under surge information sharing, regret occurs only when the foregone region surges in Stage 2. We observe that while the overall excess movement in the surge treatment can be explained by regret aversion, the regret model predicts that this would primarily stem from Zone 1 drivers, and not from Zone 2 drivers as we find in our experiments. The intuition is that Zone 1 drivers are unlikely to experience disutility from relocation because the probability of Zone 1 surging in Stage 2 is very low due to the high oversupply in Zone 1, but there is considerable chance for Zone 3 continuing to surge in Stage 2, which would induce disutility from staying on Zone 1 drivers. Moreover, decisions of Zone 1 drivers under local information sharing are unlikely to be explained by regret aversion since these drivers never receive feedback on their foregone zone, even if it surges in Stage 2. This leads us to preclude regret aversion as an explanation of our observations.

We hypothesize that two behavioral influences can provide a rationale for our experimental observations: (i) *mental accounting* (Thaler 1999) and *loss aversion* (Kahneman and Tversky 1979), and (ii) drivers' susceptibility to *decision errors*. We first consider mental accounting and loss aversion. Note in our setting that drivers who relocate experience a temporal separation between incurring the relocation cost in Stage 1 and receiving a payment for serving a customer in Zone 3 upon being matched, which happens in Stage 2. Prior literature (Ho and Zhang 2008) suggests that such a separation can lead drivers to evaluate the prospect of moving through two separate mental accounts—one for the relocation cost and the other for the expected payment upon relocation. Moreover, if drivers are loss averse, they may weigh the upfront loss due to the relocation cost more heavily than the subsequent payment. In the absence of competition among drivers, loss aversion would lead drivers to discount the total expected utility of moving. Furthermore, this direct effect of loss aversion would be stronger for Zone 1 drivers since they incur a higher cost of relocation than Zone 2 drivers. In the presence of competition among drivers, however, the effect of loss aversion is nontrivial, and it is possible that while Zone 1 drivers choose to relocate less often due to loss aversion, the reduced competition in Zone 3 may encourage a greater tendency to relocate by Zone 2 drivers. Therefore, mental accounting and loss aversion can help to explain the rationale for Zone 2 drivers' decisions in the surge and local treatments. Second, we suspect drivers to be prone to decision errors. This can be particularly apparent for Zone 1 drivers in the local treatment, as they make decisions in the absence of any demand information and under high uncertainty. Furthermore, decision errors can help to capture the visual evidence for behavior presented in Figure 2.5 on the full treatment (i.e., greater volume of relocation than theory when the predicted volume of relocation is low, and lower volume of relocation otherwise).

To capture drivers' mental accounting and loss aversion, we assume that a driver separates the relocation cost from the subsequently achievable expected payment while evaluating the total expected utility of moving. Following the prior literature (Becker-Peth et al. 2013; Zhang et al. 2016; Ho and Zhang 2008), we assume that drivers multiply the relocation cost with a loss aversion parameter $\beta \geq 1$ in calculating the disutility from incurring the relocation cost. When $\beta = 1$, drivers' behavior coincides with the rational model. We modify the equilibrium conditions in Propositions 1, 2, and 3 to capture the expected utility of staying and relocating, and compute the behavioral equilibria for the three treatments numerically.

Consistent with previous literature (Jiang et al. 2021), we interpret the proportion of drivers relocating in equilibrium as an individual's probability of relocating. We assume that under loss aversion, the decision of a driver i in period t in Zone 1, v_{it}, follows a Bernoulli distribution and takes value 1 with probability θ_{1LA}, and 0 with probability $(1 - \theta_{1LA})$, with the value of 1 indicating a decision to move. Similarly, for a driver j in Zone 2, the decision variable $w_{jt} = 1$ with probability θ_{2LA}, and $w_{jt} = 0$ otherwise. The probability mass functions for Zone 1 and Zone 2 drivers' decision are given respectively by $f(v_{it}; \beta) = [\theta_{1LA}(\beta, I_{it})]^{v_{it}}[1 - \theta_{1LA}(\beta, I_{it})]^{1-v_{it}}$, and $f(w_{jt}; \beta) = [\theta_{2LA}(\beta, I_{jt})]^{w_{jt}}[1 - \theta_{2LA}(\beta, I_{jt})]^{1-w_{jt}}$. Here, $\theta_{1LA}(\beta, I_{it})$ and $\theta_{2LA}(\beta, I_{jt})$ are the proportions of drivers predicted to leave Zone 1 and Zone 2, respectively, when the loss aversion parameter is β, and I_{it} and I_{jt} contain the demand–supply mismatch information shared by the platform with driver i in Zone 1 and driver j in Zone 2, respectively, in period t.

Drivers' decision errors are captured with the parameter ϵ, which indicates the balance between drivers' loss aversion and their susceptibility to decision errors. That is, drivers' decisions are purely based on mental accounting and loss aversion when $\epsilon = 0$, whereas drivers fully randomize between staying and moving when $\epsilon = 1$. Accordingly, motivated by prior literature, the total negative log-likelihood is given by:

$$L(\beta, \epsilon) = -Log\Bigg[\prod_{t=1}^{40}\prod_{i=1}^{N_1}\prod_{j=1}^{N_2}\Bigg\{\Big[(1-\epsilon)\cdot f(v_{it};\beta)+0.5\cdot\epsilon\Big]\cdot\Big[(1-\epsilon)\cdot f(w_{jt};\beta)+0.5\cdot\epsilon\Big]\Bigg\}\Bigg], \quad (2.18)$$

where N_1 and N_2 denote the initial number of driver-participants in Zones 1 and 2, respectively.

For the observed data, we estimate the loss aversion and the decision error parameter in (Equation 2.18) for all three treatments together using the Maximum Likelihood Estimation approach. Table 2.8 shows the estimation results for the rational equilibrium model, the loss aversion equilibrium model[11], a model involving decision errors only, and the full model that combines the

[11]In instances wherein the model predicts that the proportion of drivers who relocate or stay is 0, we perturb those

loss aversion equilibrium and drivers' decision errors. The estimated behavioral parameters are significant in all models. Furthermore, the Likelihood Ratio Test results, and the AIC and BIC values strongly suggest that the full behavioral model overall captures the experimental observations significantly better than nested models corresponding to rational theory, loss aversion only, or decision errors only.

Table 2.8: Behavioral model estimation results

	Rational Model (1)	Loss Aversion (2)	Decision Errors (3)	Loss Aversion & Decision Errors (Full Model) (4)
β		**1.65****(0.068)		**1.70****(0.167)
ϵ			**0.358****(0.003)	**0.350****(0.003)
$L(\beta, \epsilon)$	3901.622	3613.522	2252.45	2219.223
χ^2 (p-val)	0.000	0.000	0.000	
AIC	7803.244	7229.044	4506.9	4442.446
BIC	7803.244	7235.318	4513.174	4463.268

Number of observations is 3920. Standard errors in parentheses. For Likelihood Ratio Tests, p-values for comparison against the Full Model are shown. †p<0.1; *p<0.05; **p<0.01.

Figure 2.6 illustrates the comparisons between the proportions of drivers relocating as predicted by the full behavioral model, as predicted by rational theory, and the corresponding proportions observed in experiments. Results are presented for surge and local treatments since deviations from theory are particularly significant for these treatments in subsection 2.6.2. For the surge treatment, the behavioral model describes Zone 2 drivers' movements much better than rational theory, while also representing Zone 1 drivers' decisions and the overall pattern of drivers' movements reasonably well. For the local treatment, the behavioral model describes Zone 1 drivers' movements better than rational theory, while also representing Zone 2 drivers' decisions and the overall pattern of drivers' movements reasonably well. Therefore, *our estimation results indicate that loss aversion through mental accounting and decision errors are likely to be influential on drivers' de-*

proportions in our estimations to an arbitrarily small positive value close to 0 to avoid taking logarithm of 0, based on similar perturbations used in the literature in regression models involving logarithms of zeros (see Nunn 2008). We verified that the estimate is robust to the perturbation.

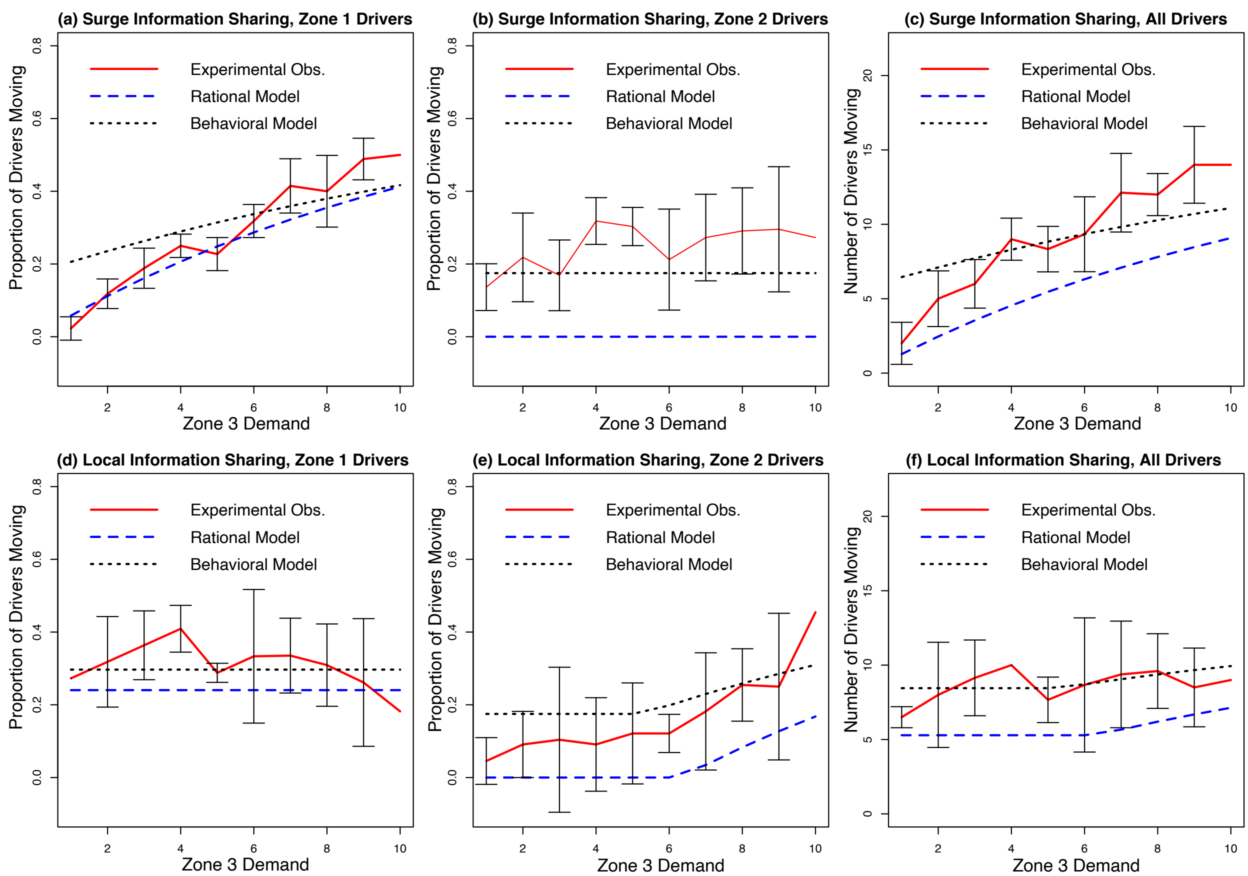


Figure 2.6: Experimental and predicted relocation probabilities

cisions, and a model incorporating these behavioral factors can better predict drivers' relocation behavior[12].

2.8 Conclusion

In this paper, we study how an on-demand service platform's spatial information-sharing mechanism affects drivers' relocation decisions and the subsequent matching efficiency. We consider three information-sharing mechanisms from theory and practice: The platform either shares demand–supply mismatch information about region(s) with excess demand with all drivers (surge information sharing), all regions with all drivers (full information sharing), or about region(s) with excess demand only with the drivers sufficiently close by (local information sharing). Surge information sharing has been adopted by several platforms around the world and is the predominant mechanism in practice, while full and local information-sharing mechanisms have been recently experimented with by some platforms, partly to create more consistent market outcomes.

Through the theoretical analysis of an equilibrium with rational drivers, we demonstrate that full information sharing results in a lower overall matching efficiency than the benchmark of surge information sharing when drivers' relocation costs are low. The rationale is that with low relocation costs, surge information sharing can mobilize sufficiently many drivers from non-surge zones to fulfill the surge demand, whereas full information sharing may hinder drivers in non-surge zones from relocating if demand conditions in drivers' own zones are revealed to be favorable. Furthermore, local information sharing is strictly dominated by at least one other mechanism (full or surge) when there is limited supply of drivers available near the surge zone; otherwise, surge information sharing performs at least just as well.

Experimentally, surge information sharing does not increase the overall matching efficiency over other information-sharing mechanisms, despite the theoretical prediction that it should. Moreover, fewer customers are served with surge information sharing than predicted by theory. The rationale is that surge information sharing results in a greater influx of drivers from nearby zones

[12]We have also explored drivers' risk aversion jointly with decision errors as a possible explanation. We omit the discussion of this model because it is significantly dominated by the full behavioral model presented in this section.

to the surge zone than theory: Although this driver influx helps to improve the matching efficiency of the surge demand, that does not compensate for the loss of matching efficiency in the non-surge zones, compromising the overall efficiency. These outcomes can limit the appeal of surge information sharing for platforms. Given the concerns raised by large cities on the congestion and pollution impacts of ride-hailing services (Benjaafar and Hu 2020), platforms may also increasingly seek to prevent redundant flocking of drivers.

Our experiments provide support for full information sharing to be a potent mechanism for improving the platform matching efficiency. With full information sharing, the platform tends to serve more customers than both standard theory and with surge information sharing, contradicting predictions. This mechanism also yields a better matching performance than local information sharing. With full information sharing, drivers respond to the demand-supply mismatch in their own zones as well as the surge zone in our experiments. As a result, drivers are motivated to move to the surge zone only when the demand-supply conditions in surge and non-surge zones collectively favor them to do so. This helps to alleviate the flocking problem and facilitate coordination among drivers, while not hurting their payoffs or utilization (as verified in Appendix subsection A.2.4). Full information sharing is also well aligned with platforms' efforts towards providing drivers with transparent earning opportunities (Uber ESG Report (2023), pp.11).

Our results also provide some empirical support for the potential benefits of local information sharing. This mechanism outperforms standard theory predictions in its efficiency to match supply and demand, while also achieving a comparable performance to surge information sharing. Interestingly, even though this mechanism creates a greater influx of drivers than theory towards the surge zone (as in surge information sharing), it is successful at mobilizing drivers from both nearby and farther zones. That helps to increase the matching efficiency in the surge zone without compromising the matching efficiency in non-surge zones as much, as farther zones have high supply relative to demand. Hence, private and targeted information dissemination mechanisms to drivers, as in local information sharing in our experiments, can indeed alleviate coordination problems among drivers, thereby validating a major motivation for their consideration in practice(Ong et al. 2021).

Behaviorally, we find that two behavioral influences, drivers' mental accounting and loss aversion, and their susceptibility to decision errors, can explain the observed deviations in our experiments. According to our behavioral model, drivers experience disutility from incurring an upfront relocation cost before they realize any earnings from serving in the surge zone, which is estimated to be about 1.7 times the actual relocation cost, and they are also subject to random errors in their relocation decisions. Drivers' decision errors can provide a rationale for the higher inclination to relocate than theory in the surge and local treatments overall, while mental accounting and loss aversion can explain why this inclination is relatively stronger for drivers in nearby zones: Loss aversion acts to counterbalance the effect of decision errors for drivers in farther zones since these drivers have higher costs of relocation. In contrast, both lower relocation costs and weaker competition from drivers farther out can make drivers from nearby zones more willing to relocate. Our results indicate that to predict drivers' relocation decisions and the availability of supply across zones better, a platform can benefit by using a behavioral equilibrium model incorporating loss aversion and decision errors.

Our work offers avenues for future work. In this paper, we have assumed a simple form of dynamic pricing structure for tractability and to facilitate participants' understanding of the experimental task. A natural extension would be to study how a platform's optimal pricing policy could be affected by its choice of information-sharing mechanism. If drivers are less eager to move due to behavioral influences under certain mechanisms, the platform may need to pay larger financial incentives to induce relocation. As a first attempt, Jiang et al. (2021) have considered how demand information sharing and accompanying financial incentives jointly influence drivers' relocation decisions in an environment involving two zones. Extending their analysis to multiple zones and spatial information-sharing mechanisms (such as those considered in this paper) will be a welcome addition. It will also be valuable to consider the customers' decisions more explicitly in our context to understand dynamics on both sides of the market.

CHAPTER 3
PAYMENT ALGORITHM TRANSPARENCY ON ON-DEMAND SERVICE PLATFORMS

3.1 Introduction

Recent years have witnessed significant growth in the range of services available to customers on-demand, some of which include ridesharing, grocery-delivery, courier-delivery, and food-delivery services. Most of these on-demand services are offered by firms adopting the role of an intermediary platform that connects service-seeking customers to service-providing agents (workers). One of the most crucial operational decisions that a platform needs to make is to determine worker compensation for each service task. A platform's practices around worker compensation are highly influential on the value that workers derive from providing their labor on the platform and their decisions to provide service for the platform or not, and ultimately on how effectively the platform can match demand and supply.

Platforms have been experimenting with different kinds of algorithms for compensating workers based on the characteristics of the service tasks they work on. Early in their conception, many platforms paid the worker fulfilling a service request a fixed portion of the price paid by the customer. This commission-based model is still used by some platforms such as Via (Via 2022), Ola (Ola New Zealand 2022), and Grab (Grab 2022). In contrast, several platforms have decoupled workers' payments from the price paid by customers and instead implemented an effort-based payment algorithm. For instance, Uber used a compensation model that paid drivers a consistent amount per unit time and distance on the trip (Kerr 2022). Similarly, Instacart's shoppers were paid a fixed amount on every order and for each item they fulfilled (Selyukh 2019). As of mid-2022, Lyft pays its drivers using per unit time and distance rates in most regions in which it operates (Lyft 2022). More recently, some platforms began implementing new algorithms that calculate workers' payments based on a variety of factors both endogenous and exogenous to the service task, and the payments generated by these algorithms do not necessarily follow the intuitive structure of the fixed-commission or effort-based payment models from the workers' perspective. For instance, Uber recently switched to using a payment algorithm that incorporates factors such as the specific route taken, traffic conditions, or whether the destination is a low demand area, in addition to the time and distance for the trip (Lemar 2022; Uber Help 2022). Other platforms opting for such enhanced algorithms include Instacart (Selyukh 2019), Target's Shipt (Kaori Gurley 2020), Walmart's Spark (Kaori Gurley 2021), and Amazon Flex (Amazon Flex 2022), to name a few. Platforms argue that by using a wider set of factors to calculate payments, they are able to better manage the customer experience (Higgins 2022; Lemar 2022; Toh 2022).

Complementary to designing an algorithm to determine workers' compensation, a platform must also decide how transparent it should make the algorithm to workers. Platforms using intuitive and relatively easy-to-explain fixed-commission or effort-based payment models have often been transparent about the details of their payment calculations. For instance, Lyft is transparent about the per unit time and distance rates it offers, and platforms such as Ola, Via, and Grab, which use a commission-based payment model, reveal the percentage commission they target. Conversely, platforms opting for enhanced but non-intuitive algorithms often keep them opaque, by concealing how the influential factors are incorporated into the payment algorithm, and in some cases, not even identifying all of the influential factors. Examples of platforms opting for such opacity include Uber (Kerr 2022), Shipt (Kaori Gurley 2020), Amazon Flex (Amazon Flex 2022), and Instacart (Selyukh 2019). Platforms may choose opacity for a variety of reasons. First, platforms cite concerns over revealing their secret recipe to their competitors as their reason for keeping their payment algorithms opaque (Möhlmann and Henfridsson 2019). Another motivation for platforms to obfuscate the details of the pay is to prevent workers from rejecting work from the platform altogether if they view pay under certain contingencies unappealing (Fischels 2021; Change.org 2022). Opacity can also be a measure to mitigate the negative reactions to the experiments and changes that a platform might implement on the payment model (Kalin 2022; Fischels 2021).

Anecdotal evidence, however, suggests that platform workers find it difficult to rationalize payment under algorithms that do not purely follow commission- or effort-based structures (Hussain 2020; Bellon 2022; Menegus 2020) and this difficulty is further exacerbated by a lack of transparency into how different factors are weighed in the algorithm to determine the pay. For instance, in online forums, some Uber drivers reported being paid significantly less than what they expected on long trips[1], complained about payments for long trips occasionally falling behind short trips, and expressed confusion over the inconsistency in how the payment relates to the ride characteristics[2]. Another Uber driver expressed their sentiment about the new pay algorithm: [3] *"... I had an airport run where I got stuck in traffic from an accident which made the ride almost 30 mins longer and it didn't change what I got paid. What we are being paid now doesn't seem to line up with our rate cards per mile and per minute charge. Even when I look at the previous rides, it doesn't show the breakdown of money earned per minute and per mile like it used to."* Instacart workers reported that under its updated algorithm, the payment per gig was constant regardless of the number of items and units in the order (Selyukh 2019). Workers on Shipt complained about not being paid sufficiently for large orders[4]. Workers have also voiced concerns that platforms tweak the payment algorithm without having to reveal the specifics of the change, which can reduce earnings for some workers or make earnings less reliable (Bhattarai 2019). Frustration with the payment algorithms and the lack of transparency have motivated some workers to pool their observations to gain a collective understanding of platforms' algorithms (MIT Media Lab 2020), as well as organize protests or boycotts to voice their demands from platforms (Shiptlist 2020; Borak 2022; Kaori Gurley 2021). New apps in support of workers are also being developed, for example, to help workers keep track of their earnings and costs and predict them for future work opportunities, or even to extract concealed payment-related information from platforms' systems (Marshall 2021; Griffith 2022).

In light of the anecdotal evidence for workers' frustration over the use of non-intuitive and

[1] https://www.reddit.com/r/uberdrivers/comments/wd5y13/is_anyone_else_noticing_the_pay_shortage_with/
[2] https://www.reddit.com/r/uberdrivers/comments/wk8wqv/rip_my_market_is_moving_to_upfront_fares/
[3] https://www.reddit.com/r/uberdrivers/comments/y65jhn/upfront_pricing_or_how_i_learned_to_quit_worrying/
[4] https://www.reddit.com/r/ShiptShoppers/comments/faq12c/v2_pay_sucks_for_large_orders_552_total_for_only/

opaque algorithms, two important questions remain: First, it is not clear whether these anecdotally-reported reactions reflect a systematic effect on workers' decisions to work for a platform and their perceptions of the platform. Second, the drivers of workers' negative reactions are not fully examined or understood. For example, if the non-intuitiveness of the algorithm is the primary driver of workers' negative reactions, then a platform may be better off avoiding such algorithms. Conversely, if the lack of transparency is the primary driver, then platforms may still operationalize non-intuitive algorithms through transparency. It is also possible that workers' disappointment may not be due to the algorithms themselves, but due to their unfavorable comparison against algorithms previously in place that were more intuitive. Hence, on account of the lack of empirical evidence, a careful analysis of workers' value for the different features of the payment algorithm is warranted. In this paper, we experimentally study how the intuitiveness of the pay algorithm to workers and its transparency affect workers' willingness to work for a platform and their perceptions of the platform.

From a platform's perspective, understanding workers' behavioral responses to payment algorithm design is crucial for managing both worker and customer experiences and for avoiding undesirable future consequences. Protests and boycotts hurt the platform's service level in the short term, and can hurt the platform's long-term ability to attract and retain workers. When workers use other forms of resistance such as deploying apps to enter the platform's system to extract information, it can destabilize the platform's system (Griffith 2022) and even prevent the platform from functioning properly. Moreover, concerns about workers' welfare can spill over to customers (Siddiqui 2021a; O'Donovan 2019) and affect a platform's ability to attract demand. Platforms' practices around their algorithms in general have also provoked governments around the world to analyze labor issues (Central Digital and Data Office 2021), and in some cases, to look for regulatory interventions (Lomas 2021).

Given these considerations, we aim to answer the following research questions in this paper: (1) How do the intuitiveness of and transparency into a payment algorithm affect workers' willingness to work for the platform and perceptions of the platform? (2) What is the effect of a change in algorithm from intuitive to non-intuitive on workers' decisions and perceptions? Does transparency help to manage the potentially negative effects of such a change?

To answer these questions, we conducted a series of incentivized experiments, in which we assumed the role of a platform offering work opportunities mimicking delivery order fulfillment in a computerized environment to participants on Prolific[5] in return for payment. An order included four item types that differed in the effort required to fulfill them. Four order compositions were possible — each with the same total number of items but different in the number of items belonging to each type, and thus, in the effort required at the order level. Easy (difficult) orders included more (less) items that required less (more) effort. Payment for an order was determined through an algorithm involving a weighted sum of the number of items belonging to each type. Using a between-subjects design, we manipulated the intuitiveness and transparency of the payment algorithm: The intuitive algorithm assigned higher weights for items requiring more effort, whereas the non-intuitive algorithm had the opposite structure. We manipulated transparency by either showing or concealing the weights used in the algorithm to participants. To measure participants' willingness to work for the platform, participants were given an endowment and asked for the maximum amount they were willing to pay to fulfill an order. At the end, participants were asked to state their perceptions about the platform. Three studies were conducted to manipulate prior pay experiences participants had with the platform.

We highlight three sets of insights. First, algorithm intuitiveness or transparency do not influence the decisions of prospective workers considering to join a platform for the first time. However, even among those workers, transparency helps to foster positive perceptions about the platform overall. Second, for workers with prior experiences of working for the platform, both the algorithm's intuitiveness to workers and its transparency are effective at sustaining engagement: These features help to reduce workers' order rejection rates and encourage them to incur higher participation costs to work for the platform. Moreover, algorithm transparency is particularly motivating for workers when the algorithm is non-intuitive, and in fact helps the platform to fully overcome

[5] https://www.prolific.co/

the drop in worker engagement attributable to implementing a non-intuitive algorithm. Third, a transparent platform experiences a drop in worker engagement immediately after switching from an intuitive to a non-intuitive algorithm, whereas an opaque platform does not. This is consistent with platforms' concerns on the challenges of algorithm experimentation under transparency. However, a platform is still better off committing to transparency irrespective of whether a change is ultimately implemented, because worker engagement achieved with transparency is at least as much as that without transparency, while transparency is more potent at motivating positive worker perceptions towards the platform.

The rest of the paper is structured as follows. In section 3.2, we discuss literature relevant to our paper. In section 3.3, we discuss the possible behavioral effects of algorithm intuitiveness and transparency. In section 3.4, we outline our experimental design. We discuss our results in section 3.5 and provide our concluding remarks in section 3.6.

3.2 Related Literature

Our paper lies at the intersection of four streams of literature: operational transparency in service and supply chain settings in operations management, human-algorithm connection in operational decision making, algorithmic control in organizations, and on-demand service platforms. On the first stream, work thus far has been largely focused on the consumer response to transparency into a firm's operations. Researchers have studied transparency in service settings for signaling service provider effort (Buell and Norton 2011; Buell et al. 2017), or sharing progress in product delivery (Bray 2020) or position in a queue (Buell 2021). In the supply chain context, research has considered how transparency into internal and external initiatives towards social and environmental responsibility (Buell and Kalkanci 2021) affect consumer perceptions and purchase behavior. Recent work has expanded the examination of operational transparency into new settings such as governmental operations (Buell et al. 2021) and crowdfunding platforms (Mejia et al. 2019), in managing relations with residents and donors, respectively.

In contrast to the aforementioned body of work, research investigating the effect of operational transparency on worker decisions and behavior has been relatively sparse. In Beer et al. (2021), authors study the effect of transparency into an organization's previous purchases on employees' procurement decisions. In Mejia and Parker (2021), authors examine the effect of transparency about riders' details on drivers' ride acceptance and cancellation decisions on a ridesharing platform. In Buell et al. (2017), authors observe that allowing service providers to see the customers they are serving leads to higher service quality and efficiency. Our paper adds to this body of work by considering how transparency into the structure of the compensation algorithms in on-demand service platforms affects worker behavior, which has not been considered so far. In contrast to the existing literature on wage transparency (Long and Nasiry 2020), where transparency entails whether information about employee wages are observable to peers at a firm, in our paper, transparency pertains to visibility of how the different components of a task are compensated for by the platform.

Secondly, our work is related to the literature on human-algorithm interaction in operational decision making. Several papers in this domain have examined this interaction in the context of forecasting. For example, in Dietvorst et al. (2015), authors find that human decision-makers often display aversion towards an algorithmic forecaster and rely more often on a human forecaster, while Dietvorst et al. (2018) investigate and suggest ways to reduce this algorithm aversion among individuals. In Lehmann et al. (2022), authors examine the role of complexity and transparency of a forecasting algorithm on an individual's decision to follow its advice. In Ibrahim et al. (2021), authors study how humans' judgement based on their private information can be elicited to better combine it with an algorithm. We point the interested reader to a review of the literature on human-algorithm forecast integration by Arvan et al. (2019). Research has also looked at how humans work with algorithms in a variety of operational settings including warehouse operations (Bai et al. 2022; Sun et al. 2022), pricing (Caro and de Tejada Cuenca 2018), and services (Bastani et al. 2021; Snyder et al. 2022). Unlike the aforementioned literature, which focuses on algorithms as decision support tools to humans, we focus on the human-algorithm interaction within the context of managing and compensating service providers on platforms.

Another relevant stream of literature is on algorithmic control in work settings. In Kellogg et al. (2020), authors survey how organizations use algorithms to direct workers by restricting and recommending, evaluate workers by recording and rating, and discipline workers by replacing and rewarding. Literature in this area largely utilizes organizational theories and qualitative methods such as interviews, surveys, and analysis of discussions on online forums to study the implications of algorithmic management on workers' experiences and relationship with the firm (Duggan et al. 2020; Wood et al. 2019; Wiener et al. 2021; Lee et al. 2015; Curchod et al. 2020; Möhlmann et al. 2021; Vallas and Schor 2020; Raval and Dourish 2016; Griesbach et al. 2019; Rahman 2021). However, unpacking workers' reactions to specific design elements of a payment algorithm (such as transparency and intuitiveness) remains challenging in this nascent literature because other factors that might also influence workers' reactions (such as past experiences with the platform or the platform's past compensation practices) cannot be fully observed or controlled. Our work contributes to this domain by using a controlled experimental environment to examine how individual elements of an algorithm used to determine workers' pay affect their willingness to work for the platform, as well as their perceptions of the platform. A related experimental paper in this domain is Kizilcec (2016), that studies how different levels of transparency into an algorithm utilized in peer assessment to determine individuals' grades affect their perceptions. While the focus of that work is on transparency as an *ex-post* explanation of outcomes provided to users, we evaluate how transparency in the form of information available *ex-ante* to workers on the compensation algorithm affects their decisions and perceptions. This definition of transparency is motivated by platform workers' understanding of it, which involves visibility on how much the different components of a task are paid for (Schuber 2022; Marshall 2021)[6],[7],[8],[9].

Lastly, our paper contributes to the literature on managing the operations of on-demand service platforms. We point the interested reader to a review of this literature by Benjaafar and Hu (2020).

[6]https://gigworkersunited.ca/gig_workers_bill_of_rights.html
[7]https://payup.wtf/instacart/delivering-inequality
[8]http://www.workingwa.org/gig-workers-speak-out-on-pay
[9]https://actionnetwork.org/petitions/payup-its-time-to-reboot-the-gig-economy?nowrapper=true&referrer=&source=

This literature predominantly explores service provider decisions on whether, where, and/or when to work under pre-specified exogenous compensation mechanisms. Our work is differentiated by examining empirically how the different features of the payment algorithms, such as intuitiveness and transparency, affect worker behavior.

3.3 Pay Algorithms, Transparency, and Worker Behavior

In evaluating how the pay algorithm's intuitiveness influences worker engagement, a platform faces non-trivial considerations. On the one hand, workers' ability to intuitively understand the algorithm behind the pay calculation can foster a sense of competence and make them feel better about its outcomes (Wu et al. 2008; Deci and Ryan 2000; Ryan and Deci 2000). Moreover, a platform's commitment to compensate for effort can improve workers' perceptions of fairness and help to foster their participation. On the other hand, it is possible that some workers are drawn to the prospect of earning unexpectedly large payouts on low effort (i.e., "windfall money"), which is more likely to occur with a non-intuitive algorithm that does not tie pay strictly to effort. Indeed, some workers on online forums express their attraction to the prospect of earning a large payout on little effort, for the psychological sense of achievement it brings[10]. For instance, some workers on Amazon Mechanical Turk reported that while most tasks paid \$1-\$2/hour, the possibility of finding rare "jackpot" tasks that paid \$10-\$20/hour prolonged their engagement with the platform (Lehdonvirta 2018). To the extent that workers are motivated to earn windfall money, a non-intuitive pay algorithm may not necessarily hurt worker engagement.

Broader literature has shown that transparency helps to enhance relationships, trust, and credibility within an organization (Bernstein 2017; Core 2001; Healy and Palepu 2001; Leuz and Wysocki 2016; Levitin 2013; Ullmann 1985). In the platform context, these findings translate into workers' more positive perceptions towards the platform and greater willingness to accept work from it when the pay algorithm is made transparent to workers. Providing upfront information about how the different components of a task are compensated in the algorithm also enables

[10] https://www.uberpeople.net/threads/2022-unicorn-ride-short-and-fast.466877/

workers to make more informed decisions about working for the platform, by helping them to better predict the amount of work they need to put into to meet their income target – which is known to motivate workers' labor-supply decisions (Allon et al. 2018). However, the impact of transparency on worker engagement is less clear when considered jointly with pay algorithms of different intuitiveness levels. On the one hand, it is possible that transparency adds more value to an algorithm that does not conform with workers' intuition compared to an intuitive algorithm, since workers may not feel the need to evaluate the transparency information carefully when their pay matches with their expectations (Kizilcec 2016). Transparency can be particularly beneficial under a non-intuitive algorithm to align workers' pay expectations with their experiences and mitigate potential disappointment. On the other hand, transparency by itself does not ensure that workers will notice or interpret the shared information accurately (Prat 2005), particularly if the shared information is not easy to understand or is inconsistent with one's expectation. If that is the case, transparency into a non-intuitive algorithm does not guarantee a positive response from workers.

For a platform considering to switch from an intuitive algorithm to a non-intuitive one, as several platforms have done in practice, it is also valuable to assess the potential effect of such a change on workers' engagement and how transparency can interact with it. A change in the algorithm is likely to create a dispersion in the pay experiences of workers, as observed in practice. For example, when Shipt implemented a change in their payment, the average worker earned more money per trip, but 41% of workers ended up earning less than they would have with the previous algorithm (Coworker.org 2020). Workers' reaction is then expected to be influenced by their individual pay experiences under the change. On the one hand, it is possible that by preparing workers early on for potentially disappointing pay outcomes after the change and by informing workers who experience disappointing pay outcomes under the change of other better prospects, transparency motivates positive perceptions and encourages workers to continue to engage. On the other hand, transparency equips workers with full information to contrast the new algorithm against the previous one, and if workers are particularly discouraged by potentially disappointing pay outcomes under the new non-intuitive algorithm, they can restrict their engagement after the change. On an opaque platform, although workers experiencing disappointing pay outcomes are likely to form poor perceptions of the platform and curtail engagement, those experiencing more favorable outcomes are likely to feel encouraged by the change to continue engaging with the platform, and the overall effect of change is thus ambiguous at the outset.

Given these considerations, we pose worker engagement in response to pay algorithm intuitiveness, transparency, and change as an empirical inquiry, which we attempt to examine through experiments presented in the next section.

3.4 Experimental Design

We conducted our experiments on Prolific, where each participant assumed the role of a worker who was offered an opportunity to fulfill grocery delivery orders in exchange for payment by a platform. As experimenters, we assumed the role of the platform and implemented algorithms with different intuitiveness and transparency levels corresponding to different treatments to pay participants.

We followed a between-subjects design wherein participants were assigned to one out of three experience conditions: In Study 1, participants had no prior experience working for the platform, which mimicked a setting where workers decided to join the platform for the first time. In Study 2, participants received some work and pay experience with the platform, after which their willingness to continue to accept work from the platform was elicited. In both studies, we followed a 2 (payment algorithm intuitiveness: intuitive, non-intuitive) x 2 (payment algorithm transparency: transparent, opaque) design for manipulating payments. In Study 3, all participants had some prior work and pay experience with the platform, and were assigned to one of the 2 (experience change: experience a change in algorithm intuitiveness from intuitive to non-intuitive, no change) x 2 (payment algorithm transparency: transparent, opaque) conditions. In the next three subsections, we describe orders, payment algorithms, and sequence of tasks in our experiments in more detail. In subsection 3.4.4, we provide a detailed overview of each study. In total, 602 participants participated in our experiments.

3.4.1 Orders

Orders mimicked those in a grocery delivery setting with four types of items differing in the effort required to fulfill them and completed through the widely-used computerized real-effort slider tasks (Gill and Prowse 2011). In particular, each item had one or two sliders that depicted the position and physical weight of the item. Subjects were asked to move the slider from the initial randomized position to the randomized required position shown for that task. By varying the length and granularity of the slider scale as well as the number of presented sliders, we create four item Types that increase in the necessary effort. Figure 3.1 shows an example of the slider task for the most difficult item (Type 4). Type 1 (2) items contain only the item position slider with values between 1 and 5 (1 to 50). Type 3 and Type 4 items add the physical weight slider. Type 3 (4) items have item position slider values between 1 and 5 (1 to 50) and physical weight slider values of $\{$16oz, 24oz, 32oz, 40oz$\}$ ($\{$0.25lb, 0.5lb, 0.75lb, $\ldots$, 4lb$\}$). There were four possible order compositions, each containing a total of 45 items, but differing in the number of items of each type. Order composition $x \in \{1, 2, 3, 4\}$ (OCx) consisted of 30 items of type x and 5 items each of the other types. Thus, OC1 required the least effort followed by OC2, OC3, and OC4.

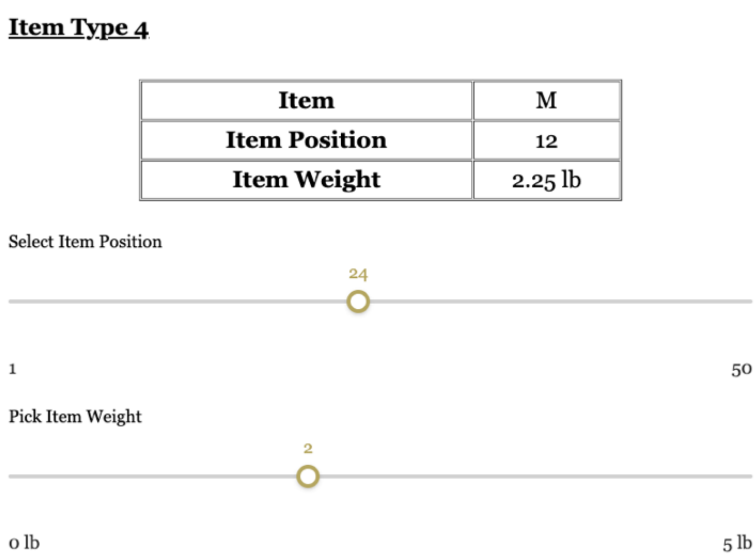


Figure 3.1: Example of a slider task for a Type 4

3.4.2 Payment Algorithm

The worker's payment for an order was determined by an algorithm consisting of the weighted sum of the number of items belonging to each type, according to:

$$\$\sum_{x=1}^{x=4}(w_x * N_x). \tag{3.1}$$

Here, w_x is the weight (per-item payment) and N_x is the number of items belonging to type $x \in \{1, 2, 3, 4\}$ in the order. The intuitiveness of the algorithm was manipulated by assigning either higher or lower weights in the algorithm for item types requiring more effort for fulfillment. Transparency of the algorithm was manipulated by either revealing or concealing weights in the algorithm. Therefore, the payment algorithm for an order possessed one of the following four possible characteristics in terms of its intuitiveness and transparency: intuitive + opaque, non-intuitive + opaque, intuitive + transparent, and non-intuitive + transparent.

To build the pay algorithms, a pre-experimental session was conducted on Prolific during which 50 subjects were asked to fulfill an order randomly selected from the four possible compositions for a fixed payment of \$2.50. We measured the amount of time it took subjects to fulfill each item type, which confirmed the ranking described above, as evident from the median fulfillment times given in Table 3.1. We then multiplied the median time (in hours) taken to complete each item type with a target payment rate of \$21.35/hour[11] to calculate the weights, and used these weights to construct the intuitive algorithm.

Table 3.1: Measurements on time taken to fulfill item types in the pre-experimental session

Item Type	Type 1	Type 2	Type 3	Type 4
Median time to fulfill (seconds)	3.9	5.1	8.4	13.7

In addition, we used the pre-experimental session to determine whether an algorithm that paid more for items requiring more effort was indeed deemed intuitive to participants. At the end of

[11] We choose this value to ensure that the minimum payment for an order (which is equal to \$1.50) covers the random cost of participation in all circumstances, which will be explained in more detail in subsubsection 3.4.4.

the pre-experimental session, we reminded participants of the four types of items, presented these item types in pairs and asked them to rate on a Likert scale which item type should be worth more in fulfillment if they were paid per item instead of a fixed amount. As evident from Table 3.2, subjects rated item types requiring more effort/time to be worth more, consistent with the intention of our design on algorithm intuitiveness.

Table 3.2: Pre-experiment participants' responses on how per-item payments should be structured

Statement	Type 3 should pay more than Type 1	Type 2 should pay more than Type 3	Type 4 should pay more than Type 2	Type 1 should pay more than Type 4
Likert-scale mean responses (1 = "strongly disagree" to 7 = "strongly agree")	5.7 (0.198)	3.2 (0.240)	5.7 (0.212)	2.4 (0.255)

Standard errors in parentheses. Note: Prior to the pre-experimental session, we anticipated that a Type 2 item would require more effort/time than a Type 3 item. Hence, a Type 2 item was labeled as "Type 3" in the pre-experiment, while a Type 3 item was labeled as "Type 2." Consequently, the pre-experiment did not elicit participants' responses on the comparison between Types 1 vs. 2, and 3 vs. 4, which are also omitted in the table.

To construct the non-intuitive algorithm, we reversed the order of the weights used in the intuitive algorithm, with item Type 1 receiving the highest and item Type 4 receiving the lowest payment weights. The implication is that low-effort items (Types 1 and 2) are worth more under the non-intuitive algorithm than the intuitive one, while high-effort items (Types 3 and 4) are worth more under the intuitive algorithm. This relation of weights between the two algorithms is consistent with observations from practice. For instance, Uber's new algorithm paid drivers less for longer trips and more on shorter trips compared to the previous algorithm that was based only on time and distance (Uber 2022). Similarly, Shipt's workers started earning less on larger orders and a bit more on smaller orders with the new algorithm than its counterpart that was based primarily on the order size (Rose Dickey 2020). Furthermore, the ranking of weights in the non-intuitive algorithm is consistent with the recent practices of some platforms as well. For instance, Instacart's workers observed that under its new algorithm, the pay offered for a batch of orders did not scale with the number of orders in the batch, effectively resulting in a lower payment per unit effort for larger batches (Silberling 2021). The details of both algorithms are presented in Table 3.3.

Table 3.3: Order compositions and algorithmic payments

Item Type	Algorithm Weights		Order Composition			
	Intuitive	Non-Intuitive	OC1	OC2	OC3	OC4
Type 1	w_1=2.31¢	w_1=8.12¢	30	5	5	5
Type 2	w_2=3.02¢	w_2=4.98¢	5	30	5	5
Type 3	w_2=4.98¢	w_3=3.02¢	5	5	30	5
Type 4	w_2=8.12¢	w_4=2.31¢	5	5	5	30
		Intuitive Pay:	\$1.50	\$1.68	\$2.17	\$2.95
		Non-Intuitive Pay:	\$2.95	\$2.17	\$1.68	\$1.50

In experimental treatments with transparency, we as the platform declared our intention to be transparent about the payment calculation and revealed the weights in the algorithm. Under opacity, the participants were aware that each item type was assigned a weight in the payment calculation. However, we informed subjects that we had decided not to reveal the weights used in the payment algorithm since we could not make our algorithm public, and concealed the weights. Furthermore, in experimental treatments where the payment algorithm was intuitive, we explained to the participants that the weights in the algorithm were based on the estimated fulfillment time per item type, whereas in treatments with a non-intuitive algorithm, no such explanation was provided. A summary of possible algorithm characteristics in the experiments, along with information provided to participants, are illustrated in Table 3.4.

Table 3.4: Possible characteristics of the payment algorithm in terms of intuitiveness and transparency

Weights in the algorithm	intuitive + opaque	non-intuitive + opaque	intuitive + transparent	non-intuitive + transparent
Intuitive explanation provided on how weights are determined?	✓	✗	✓	✗
Weights revealed?	✗	✗	✓	✓
Reason for choice of transparency level provided?	✓	✓	✓	✓

At the time an order is offered to a worker, a platform does not have perfect knowledge about the effort that will be required to fulfill it. For instance, a ridesharing platform does not know perfectly the time a driver will spend on a ride request since governing factors such as traffic and rider punctuality are outside of their control. In the grocery delivery context, this uncertainty can arise from various factors including stock-outs and replacements, customer requests for changes in the order during fulfillment, and the platform's lack of perfect visibility into the store layout. As a result, the final payment to the worker is random and many platforms show the payment offer for an order only in the form of a range (Avedian 2022; Financial Panther 2021). Consistently, when the participants were offered the opportunity to work on orders in our experiments, they were shown the four possible order compositions and a range for the potential payment. Each order composition is realized with equal probability, which guarantees an equivalent distribution of final payments across the treatments with intuitive and non-intuitive algorithms. However, we do not reveal the full distribution of potential payments to participants for consistency between transparent and opaque treatments.

3.4.3 Sequence of Experimental Tasks

Participants were first given preliminary instructions about the experiment, followed by the consent form and detailed instructions. Participants had to answer the questions of a comprehension quiz correctly to proceed. Participants were then acquainted with the four item types in a trial phase, after which they proceeded to the main experiment. Participants were assigned to one of the three experience conditions captured by Study 1-3. In each study, participants were randomly assigned to treatments with different algorithmic features of intuitiveness and transparency, and made decisions on accepting work from the platform. The detailed sequence of events followed in each of these studies will be described in more detail in the next section.

Following the main experiments, subjects were given a post-experiment questionnaire involving questions about their perceptions about the platform. Specifically, we asked participants to rate their perceptions of trust, sincerity, fairness, and favorability towards the platform, their perception of the accuracy of information shared by the platform, and the attractiveness of the platform as an employer on a Likert scale. These items are presented in detail in Appendix subsection B.1.1.

After the post-experiment questionnaire, participants' risk preferences were measured with the multiple price list method (Holt and Laury 2002). Participants earned a small bonus based on the outcome of the risk preference elicitation task over their earnings from the experiment. Details are included in Appendix subsection B.1.2. Finally, they were asked to respond to a demographic survey that included questions about their age, gender, education, and income.

3.4.4 Overview of Experiments

Study 1

In Study 1, we focused on how the payment algorithm intuitiveness and transparency affect worker behavior when workers have no prior experience of working for the platform. This study is designed to mimic a setting where workers were deciding whether to join a platform for the first time. The study was completed by 200 participants who were randomly assigned to one of the four treatments pertaining to payment algorithm characteristics (i.e., intuitive + opaque, non-intuitive + opaque, intuitive + transparent, and non-intuitive + transparent).

Each participant received a base pay of \$1 and initial endowment of \$1.50, which could be spent towards participating in the work opportunities offered by the platform. Participants were first shown a summary of the platform's operations and were informed that their payment would be calculated according to Equation 3.1. Participants assigned to a transparency treatment could also observe the exact value of the weights to be used in the payment calculation, whereas in the opaque algorithm treatments, weights were hidden. Second, participants were shown a summary of the possible order compositions, which described the number of different item types in each possible order. Participants were informed that depending on the order composition assigned to them, their payment from fulfilling the order would be in the range of \$1.50 to \$2.95.

In the third step, participants were asked to enter the maximum amount they were willing to pay to fulfill an order for the platform. Participants were informed that they would incur a participation cost to work on the order, which would be randomly drawn between \$0 and \$1.50, and the order would be assigned to them if and only if their willingness-to-pay (WTP) was greater than or equal to their participation cost. Thus, we used the Becker-DeGroot-Marschak mechanism to measure participants' true value from working for the platform (Becker et al. 1964). WTP elicitation screens from our experimental interface are illustrated in Appendix subsection B.1.3. Values of the payment weights were chosen to guarantee that earnings from fulfilling an order always exceeded the base pay. After the WTP elicitation, the participation cost was drawn, and participants were informed about the outcome. Subjects whose WTP was greater than or equal to the participation cost proceeded to work on the order. After completing the order, an order receipt was displayed, including the number of fulfilled items by type, the payment from the platform, the participation cost incurred, the net earnings on the order, and the net payoff including the initial endowment. The receipt also included information on the platform's gains (completed order and data of the participant's work on the order) and costs (payment for the order). Subjects whose WTP was less than the participation cost were not assigned an order and kept their endowment. At the end of the experiment, participants filled out a post-experiment questionnaire about their perceptions of the platform. They were then shown their experimental earnings and proceeded to complete the risk preference elicitation task and demographic survey.

Study 2

Unlike Study 1, Study 2 evaluates how the payment algorithm intuitiveness and transparency affect worker behavior after workers gain some work and pay experience with the platform[12]. This study was completed by 201 participants. Study 2 closely followed the treatments and procedures in Study 1, except that participants were presented two consecutive orders and were endowed with $3 to use towards their participation. Participants were required to fulfill the first order, and hence, no WTP was elicited for the first order. To avoid any anchoring effects on the magnitude of the participation cost for the first order, all participants incurred $1.50 towards fulfilling that order. After fulfilling the first order, participants were offered a second order, for which their WTP

[12]By conducting a separate study to analyze the effect of algorithmic features on worker behavior after workers gain some work and pay experience instead of eliciting participants' WTP multiple times in a single study, we avoid potential bias in results due to workers' experience not being fully exogenous.

was elicited. The rest of the procedures, including the post-experiment questionnaire and the risk elicitation task, were identical to Study 1.

Study 3

Study 3 is designed to help answer: (1) How does an algorithm change (from intuitive to non-intuitive) affect participants' willingness to work for the platform?, (2) Can transparency help to alleviate the potentially negative effects of such a change? As such, all participants were assigned to one of the 2 (experience change: experience a change in algorithm intuitiveness from intuitive to non-intuitive, no change) x 2 (payment algorithm transparency: transparent, opaque) conditions. The study was completed by 201 participants.

In addition to a base pay of $1, subjects were endowed with $4.5, which they could use towards their participation to fulfill orders for the platform. Participants were shown three consecutive orders. Participants were required to fulfill the first and the second order; no WTP was elicited for these orders. Participants incurred $1.50 towards fulfilling each of the first two orders. In all treatments, an intuitive payment algorithm was used for the first order. In treatments with algorithm change, the platform announced after the first order that a different algorithm would be used to determine payment for future orders and the non-intuitive algorithm was used in the second order onward. In treatments without change, participants were not provided any new information as they proceeded to the second order. For the third order offered to participants, their WTP was elicited following a similar procedure to Studies 1 and 2. All other procedures were similar to those in Study 1 including the same post-experiment questionnaire and risk preference elicitation tasks.

In addition to the perception questions outlined in subsection 3.4.3, subjects who experienced a change in algorithm were asked for their perceptions associated with the change. In particular, we measured participants' perceptions on the fairness of the change, appropriateness of the new algorithm compared to the previous one, and their perceptions about how earnings under the two algorithms compare to each other. These items are presented in detail in Appendix subsection B.1.1.

3.5 Results

Dependent Variables: To capture participant i's willingness to work for the platform, we use two sets of dependent variables in our regression analyses. First, the rejection decision is captured with *Reject*$_i$, which equals 1 if the participant's WTP is \$0, and equals 0 otherwise. Second, participant i's WTP is captured with *WTP*$_i$.

To capture participants' perceptions of the platform, we rely on their responses to the post-experiment questionnaire. For platform trust, we create a variable *Trust*$_i$ by averaging the responses on the four items measuring platform trust, and we create the variables *Sincerity*$_i$ and *Favorability*$_i$ in a similar manner, as Cronbach's α displays sufficiently high reliability across these items ($\alpha-$values are reported in Table B.1 in Appendix subsection B.1.1). We use scores on platform fairness, correctness of information shared by the platform, and attractiveness to work for as is to create the variables *Fairness*$_i$, *Info-correctness*$_i$, and *Work-attractiveness*$_i$, respectively. For participants who see a change in the algorithm in Study 3, we use the responses as is on questions about the fairness of the change, the appropriateness of the new algorithm, and whether the algorithm used initially pays more, to create the variables *New_fair*$_i$, *New_appropriate*$_i$, and *Oldpaysmore*$_i$, respectively.

3.5.1 Analysis and Results: Study 1

To study the overall effect of algorithm intuitiveness and transparency, we model workers' willingness to work for the platform and perceptions of the platform as a function of the intuitiveness and transparency level in the treatment they observed. In particular, we estimate:

$$Engagement_i = Constant + \alpha_1 Transparent_i + \alpha_2 Intuitive_i + \epsilon_i, \tag{3.2}$$

where $\textit{Engagement}_i \in \{\textit{Reject}_i, \textit{WTP}_i\}$, $\textit{Intuitive}_i$ equals 1 if the intuitive algorithm is used in the treatment observed by participant i, and 0 otherwise and $\textit{Transparent}_i$ equals 1 if the platform revealed the weights in the algorithm, and 0 otherwise.

We estimate a different model for workers' perceptions because no order is completed prior to elicitation of WTP, whereas participants state their perceptions at the end of the experiment. Thus, we add controls for the difficulty of the assigned order:

$$\textit{Perception}_i = \textit{Constant} + \beta_1 \textit{Transparent}_i + \beta_2 \textit{Intuitive}_i + \beta_3 \textit{Easy}_i + \beta_4 \textit{Difficult}_i + \epsilon_i. \quad (3.3)$$

where $\textit{Easy}_i$ equals 1 if participant i completed an easy order (i.e., OC1 or OC2) and 0 otherwise and $\textit{Difficult}_i$ equals 1 if participant i completed a difficult order (i.e OC3 or OC4) and 0 otherwise. When an order was not assigned to the participant, both $\textit{Easy}_i$ and $\textit{Difficult}_i$ equal 0.

Algorithm transparency helps to motivate positive perceptions about the platform irrespective of the algorithm's intuitiveness to workers

Results are reported in Table 3.5. Columns (1) and (2) show no significant effect of the algorithm's intuitiveness or its transparency on participants' rejection decisions or their WTP. Columns (3)-(8) indicate that the algorithm's intuitiveness to workers does not affect their perceptions of the platform; however, we observe that transparency plays a significant role in fostering positive perceptions.

To examine the differential role of transparency in managing worker engagement under intuitive versus non-intuitive algorithms, we add the interaction term $\textit{Intuitive}_i \times \textit{Transparent}_i$ to models Equation 3.2 and Equation 3.3. Thus, $\textit{Transparent}_i$ captures the value created by transparency in the baseline case where the algorithm is non-intuitive, while $\textit{Transparent}_i + \textit{Intuitive}_i \times \textit{Transparent}_i$ captures the value created by transparency when the algorithm is intuitive. Results in Table 3.6 show that irrespective of the intuitiveness of the algorithm, transparency directionally increases workers' willingness to pay and reduces the likelihood of rejection, but these effects are

Table 3.5: Effect of algorithm intuitiveness and transparency, Study 1

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.023	-0.067	-0.282	-0.045	-0.136	0.005	-0.177	-0.187
	(0.024)	(0.058)	(0.188)	(0.214)	(0.215)	(0.197)	(0.199)	(0.223)
Transparent	-0.022	0.075	0.399**	0.897***	0.708***	0.643***	0.572***	0.640***
	(0.024)	(0.058)	(0.188)	(0.214)	(0.215)	(0.197)	(0.199)	(0.223)
Easy			1.026***	0.902***	0.931***	0.751***	1.158***	1.352***
			(0.217)	(0.247)	(0.249)	(0.228)	(0.230)	(0.257)
Difficult			1.072***	0.923***	0.997***	0.884***	1.007***	1.277***
			(0.271)	(0.308)	(0.311)	(0.285)	(0.287)	(0.322)
Constant	0.052**	0.800***	4.077***	3.318***	3.684***	4.192***	3.579***	3.196***
	(0.022)	(0.052)	(0.187)	(0.212)	(0.214)	(0.196)	(0.197)	(0.221)
Observations	200	200	200	200	200	200	200	200

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 3.6: Role of transparency in managing engagement and perceptions under different algorithms, Study 1

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.008	-0.082	-0.441*	0.035	-0.142	0.150	-0.121	-0.092
	(0.034)	(0.083)	(0.266)	(0.303)	(0.306)	(0.280)	(0.282)	(0.316)
Transparent	-0.007	0.060	0.239	0.978***	0.703**	0.789***	0.630**	0.736**
	(0.035)	(0.083)	(0.267)	(0.304)	(0.307)	(0.281)	(0.283)	(0.317)
Intuitive × Transparent	-0.029	0.029	0.318	-0.161	0.011	-0.289	-0.113	-0.190
	(0.049)	(0.117)	(0.376)	(0.428)	(0.432)	(0.395)	(0.399)	(0.447)
Easy			1.022***	0.905***	0.931***	0.755***	1.159***	1.354***
			(0.217)	(0.247)	(0.249)	(0.228)	(0.230)	(0.258)
Difficult			1.069***	0.925***	0.996***	0.888***	1.008***	1.280***
			(0.271)	(0.309)	(0.312)	(0.285)	(0.288)	(0.323)
Constant	0.044*	0.808***	4.166***	3.273***	3.687***	4.110***	3.547***	3.143***
	(0.026)	(0.061)	(0.215)	(0.244)	(0.246)	(0.225)	(0.227)	(0.255)
Observations	200	200	200	200	200	200	200	200
Linear Hypotheses Tests:								
Transparent + (Intuitive × Transparent)	-0.0364	0.089	0.560**	0.817***	0.714**	0.500*	0.517*	0.546*
	(0.034)	(0.082)	(0.265)	(0.301)	(0.304)	(0.278)	(0.281)	(0.314)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

not statistically significant. In contrast, transparency significantly improves workers' perception about the platform: When the algorithm is non-intuitive, transparency improves all perception metrics significantly except for trust, and when the algorithm is intuitive, transparency has a positive and significant effect on trust, sincerity, and fairness, and has a positive and marginally significant effect on all other perception metrics.

Overall, we find that for workers considering joining a platform for the first time, algorithm intuitiveness or transparency does not seem to play a significant role on workers' decisions. However, transparency helps to motivate positive perceptions about the platform regardless of the intuitiveness of the payment algorithm, which likely creates value for the platform in the long run.

Robustness: Since our experimental manipulation of transparency varies the amount of information that participants have about the algorithm, our results can potentially be affected by participants' risk aversion. Even though subjects were randomly assigned to different treatments, participant heterogeneity could also play a role in the results. Appendix section B.3 shows consistent results after controlling for risk aversion and participant demographics.

3.5.2 Analysis and Results: Study 2

Recall that participants in Study 2 were required to fulfill the first order and their WTP was elicited for the second order. Therefore, Study 2 captures workers' willingness to accept work from the platform after gaining some experience of being compensated by the platform's algorithm.

We examine the effect of the algorithm's intuitiveness and its transparency following a similar approach to Study 1. Our regression model for $\mathit{Engagement}_i \in \{\mathit{Reject}_i, \mathit{WTP}_i\}$ is:

$$\mathit{Engagement}_i = \mathit{Constant} + \gamma_1 \mathit{Transparent}_i + \gamma_2 \mathit{Intuitive}_i + \gamma_3 \mathit{Difficult}_{1i} + \epsilon_i. \tag{3.4}$$

In this model, $\mathit{Difficult}_{1i}$ equals 1 if the first order completed by participant i was a difficult one (i.e., OC3 or OC4) and 0 otherwise. This term is included as a control for the participant's experience with the first order. To evaluate the effect on perceptions, we use the regression model below:

$$\begin{aligned}\mathit{Perception}_i = \mathit{Constant} + \delta_1 \mathit{Transparent}_i + \delta_2 \mathit{Intuitive}_i + \delta_3 \mathit{Difficult}_{1i} + \delta_4 \mathit{Easy}_{2i} + \\ \delta_5 \mathit{Difficult}_{2i} + \epsilon_i.\end{aligned} \tag{3.5}$$

In this model, we control for the participants' experiences with both first and second orders as participants are asked to state their perceptions of the platform at the end of the experiment.

Algorithm intuitiveness and transparency both help to sustain workers' engagement with the platform

Results are reported in Table 3.7. Both algorithm intuitiveness and transparency significantly increase workers' engagement with the platform. As evident from column (1), when the algorithm is transparent, workers are less likely to reject the second order from the platform. Specifically, while 16 out of 100 participants rejected a second order under opacity, only 4 out of 101 did so when the platform was transparent. Furthermore, as evident from column (2), workers are willing to incur a marginally higher participation cost to work for the platform when the algorithm is intuitive. Columns (3)-(8) show that transparency strongly improves perceptions, whereas algorithm intuitiveness does not significantly influence these metrics.

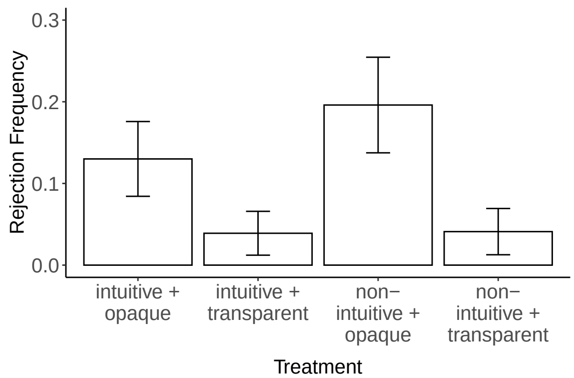
Table 3.7: Effect of algorithm intuitiveness and transparency, Study 2

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.034	0.133*	0.034	0.193	0.093	0.086	0.088	-0.200
	(0.042)	(0.070)	(0.207)	(0.225)	(0.228)	(0.205)	(0.208)	(0.238)
Transparent	-0.121***	0.099	0.628***	1.143***	0.611***	0.438**	0.811***	0.981***
	(0.042)	(0.070)	(0.206)	(0.224)	(0.226)	(0.204)	(0.207)	(0.237)
Difficult_1	-0.017	0.047	-0.116	-0.128	-0.131	-0.022	-0.163	-0.079
	(0.042)	(0.070)	(0.205)	(0.223)	(0.225)	(0.203)	(0.206)	(0.235)
Easy_2			0.891***	0.957***	0.761***	0.962***	0.958***	1.255***
			(0.252)	(0.274)	(0.277)	(0.250)	(0.253)	(0.289)
Difficult_2			0.955***	1.008***	1.051***	0.995***	1.115***	1.339***
			(0.250)	(0.271)	(0.274)	(0.247)	(0.251)	(0.286)
Constant	0.187***	0.660***	3.959***	2.887***	3.571***	4.195***	3.512***	2.989***
	(0.042)	(0.071)	(0.224)	(0.243)	(0.246)	(0.222)	(0.225)	(0.257)
Observations	201	201	201	201	201	201	201	201

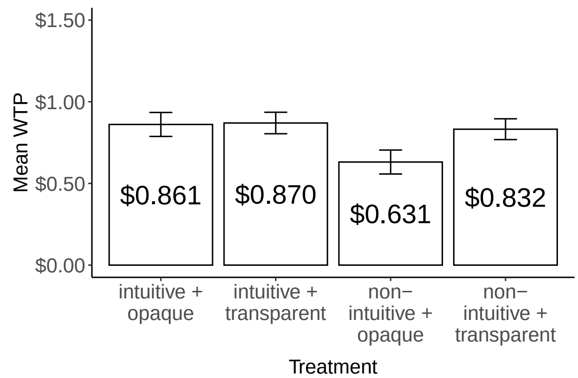
Standard errors in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$

Transparency is particularly effective at sustaining workers' engagement under a non-intuitive algorithm

We next consider the differential role of transparency in sustaining workers' engagement under intuitive versus non-intuitive algorithms. Figure 3.2a and Figure 3.2b illustrate the rejection frequency and mean WTP for the second order under different intuitiveness and transparency conditions. As evident from Figure 3.2a, transparency helps to reduce the rejection rate among workers



(a) Rejection frequency per treatment



(b) Mean WTP per treatment

Figure 3.2: Study 2 Rejection frequency and Mean WTP across conditions of algorithm change. Bars indicate standard errors

under both types of algorithms; however, this effect is particularly large under the non-intuitive algorithm. Interestingly, Figure 3.2b demonstrates that transparency increases participants' WTP on average when the algorithm is not intuitive, while transparency has no substantial effect with an intuitive algorithm. In fact, participant WTP facing a transparent but non-intuitive algorithm is comparable on average to that under an intuitive algorithm, meaning that participants do not seem to punish the platform for using a non-intuitive algorithm as long as the platform reveals the weights in the algorithm.

We study the differential role of transparency formally by including the interaction term $Intuitive_i \times Transparent_i$ into models (Equation 3.4) and (Equation 3.5). Results reported in Table 3.8 generally agree with our observations from Figure 3.2. Columns (1) and (2) show that transparency helps to reduce workers' likelihood of rejection and increases their WTP on a second order when the payment algorithm is not intuitive to workers. In contrast, under an intuitive algorithm, transparency has a directionally consistent but insignificant effect, which is verified using a linear hypothesis test on the sum of coefficients on *Transparent* and *Intuitive* x *Transparent* (as demonstrated in the second-to-last row of Table 3.8). We further assess whether transparency creates sufficient value for workers to alleviate the reduced willingness to work under a non-intuitive algorithm. In column (2) of Table 3.8, the coefficient of *Intuitive* is positive and significant, implying that workers' willingness to work under a non-intuitive algorithm is lower than under an

Table 3.8: Role of transparency in managing engagement under the algorithms, Study 2

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.066	0.229**	-0.190	0.039	0.010	-0.194	-0.157	-0.194
	(0.059)	(0.099)	(0.294)	(0.320)	(0.324)	(0.291)	(0.295)	(0.339)
Transparent	-0.154**	0.199**	0.394	0.982***	0.525	0.145	0.555*	0.988***
	(0.061)	(0.101)	(0.300)	(0.326)	(0.331)	(0.297)	(0.301)	(0.345)
Intuitive × Transparent	0.063	-0.190	0.441	0.303	0.162	0.552	0.481	-0.012
	(0.084)	(0.139)	(0.411)	(0.447)	(0.453)	(0.407)	(0.412)	(0.473)
Difficult_1	-0.016	0.045	-0.113	-0.126	-0.129	-0.018	-0.160	-0.079
	(0.042)	(0.069)	(0.205)	(0.223)	(0.226)	(0.203)	(0.206)	(0.236)
Easy_2			0.911***	0.970***	0.768***	0.986***	0.979***	1.254***
			(0.253)	(0.275)	(0.278)	(0.250)	(0.253)	(0.291)
Difficult_2			0.962***	1.013***	1.053***	1.004***	1.123***	1.339***
			(0.250)	(0.271)	(0.275)	(0.247)	(0.250)	(0.287)
Constant	0.204***	0.609***	4.072***	2.964***	3.612***	4.336***	3.635***	2.985***
	(0.048)	(0.080)	(0.247)	(0.269)	(0.272)	(0.245)	(0.248)	(0.284)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Transparent + (Intuitive × Transparent)	-0.091	0.009	0.835***	1.285***	0.687**	0.697**	1.037***	0.976***
	(0.058)	(0.096)	(0.283)	(0.307)	(0.311)	(0.280)	(0.283)	(0.325)
Intuitive + (Intuitive × Transparent)	-0.003	0.039	0.251	0.342	0.172	0.357	0.325	-0.206
	(0.059)	(0.098)	(0.290)	(0.315)	(0.319)	(0.286)	(0.290)	(0.333)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

intuitive algorithm when the platform is opaque. In contrast, the sum of the estimates for *Intuitive* and *Intuitive* x *Transparent* in columns (1) and (2) are not significantly different from 0 as demonstrated in the last row of Table 3.8, which implies that when the platform is transparent about the underlying payment calculation, workers' engagement facing a non-intuitive algorithm is comparable to that facing an intuitive algorithm.

Results in columns (3)-(8) in Table 3.8 show that when the algorithm is non-intuitive, transparency boosts workers' perceptions of the platform about its sincerity, favorability, and work-attractiveness. Using linear hypothesis test on the sum of coefficients on *Transparent* and *Intuitive* x *Transparent*, we identify that when the algorithm is intuitive to workers, transparency has a significant role in improving all of the perceptions considered ($p < 0.05$ in all metrics).

Taken together, our results suggest that transparency is particularly effective at sustaining engagement under algorithms that are inherently difficult for workers to rationalize. Transparency can help a platform overcome the potential downsides associated with a non-intuitive algorithm and result in an equivalent willingness to work as when the platform uses an intuitive algorithm. With respect to managing workers' perceptions, transparency tends to be beneficial overall, regardless of the algorithm intuitiveness.

Transparency helps to manage workers' experiences with unfavorable pay outcomes under a non-intuitive algorithm

Next, we explore why transparency is particularly effective in sustaining workers' engagement when the platform uses a payment algorithm that is not intuitive to workers. One conjecture is that transparency reduces the effect of workers' disappointing pay experiences under the non-intuitive algorithm, since knowing the payment possibilities for different order compositions in advance can help prepare workers for future outcomes. It is also possible that transparency helps to draw workers' attention towards the prospect of earning a large payment with relatively little effort. This can be particularly salient for workers who have not had such a favorable experience in the past. In our setting, a worker who was previously assigned a difficult order (OC3 or OC4) under the non-intuitive algorithm is more likely to have an unfavorable experience, whereas a worker previously assigned to an easy order (OC1 or OC2) under the non-intuitive algorithm has a more favorable experience. This is because the non-intuitive algorithm sets payment for difficult (easy) orders towards the lower (upper) end of the range of payment. Consequently, we investigate how transparency affects behavior and perceptions of workers with different previous pay experiences. For this purpose, we introduce the interaction terms $\textit{Intuitive}_i \times \textit{Difficult}_{1i}$ and $\textit{Transparent}_i \times \textit{Difficult}_{1i}$ to the specification used in Table 3.8.

The results in Table 3.9 show that transparency helps to reduce the rejection rates and increase WTP among workers who had a disappointing pay experience with the non-intuitive algorithm, i.e., the sum of the coefficients *Transparent* and *Transparent* x $\textit{Difficult}_1$ in columns (1) and (2) in the last row in the table is statistically significant. Furthermore, transparency improves perceptions of sincerity and work-attractiveness significantly, and marginally improves favorability for the same group of workers. Considering workers with favorable pay experiences with a non-intuitive algorithm, we observe consistent, yet more muted effects of transparency: As evident from the coefficient *Transparent* in columns (1) and (2) in Table 3.9, transparency reduces workers' rejection rate significantly, but has a non-significant effect on WTP for this group of workers. Transparency also boosts perceptions of sincerity and work-attractiveness significantly among the same group of workers, as evident from columns (3)-(8).

Table 3.9: Role of transparency in managing the effect of experience, Study 2

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	0.054	0.054	-0.314	0.124	-0.225	-0.369	-0.380	-0.592
	(0.071)	(0.118)	(0.356)	(0.386)	(0.391)	(0.351)	(0.356)	(0.406)
Transparent	-0.171**	0.166	0.363	0.860**	0.549	0.224	0.477	0.880**
	(0.072)	(0.121)	(0.365)	(0.396)	(0.400)	(0.360)	(0.365)	(0.416)
Difficult_1	0.100	-0.185	-0.291	-0.151	-0.382	-0.142	-0.504	-0.659
	(0.073)	(0.122)	(0.367)	(0.399)	(0.403)	(0.363)	(0.367)	(0.419)
Intuitive × Transparent	0.067	-0.197	0.434	0.307	0.149	0.543	0.469	-0.035
	(0.082)	(0.137)	(0.413)	(0.449)	(0.454)	(0.408)	(0.413)	(0.471)
Transparent × Difficult_1	0.025	0.081	0.080	0.233	-0.016	-0.135	0.188	0.272
	(0.082)	(0.137)	(0.412)	(0.447)	(0.452)	(0.407)	(0.412)	(0.470)
Intuitive × Difficult_1	-0.244***	0.360***	0.264	-0.176	0.499	0.368	0.477	0.849*
	(0.082)	(0.137)	(0.419)	(0.456)	(0.460)	(0.414)	(0.419)	(0.478)
Easy_2			0.892***	0.988***	0.731**	0.956***	0.947***	1.195***
			(0.256)	(0.278)	(0.281)	(0.253)	(0.256)	(0.292)
Difficult_2			0.935***	1.036***	0.999***	0.962***	1.075***	1.252***
			(0.255)	(0.277)	(0.280)	(0.252)	(0.255)	(0.291)
Constant	0.148***	0.720***	4.166***	2.969***	3.751***	4.410***	3.815***	3.292***
	(0.055)	(0.092)	(0.293)	(0.318)	(0.322)	(0.289)	(0.293)	(0.334)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Transparent+	-0.146**	0.246**	0.443	1.093***	0.533	0.089	0.665*	1.152***
(Transparent × Difficult_1)	(0.073)	(0.122)	(0.366)	(0.398)	(0.402)	(0.362)	(0.366)	(0.418)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

These observations lead us to conclude that while transparency helps to sustain worker engagement under non-intuitive algorithms in general, it is particularly effective at managing workers' experiences with unfavorable pay outcomes under these algorithms.

Robustness: As before, Appendix section B.3 shows consistent results after controlling for risk aversion and participant demographics. Loss aversion is another possible reason for workers' lower willingness to work under the non-intuitive algorithm. Under this algorithm, workers can construe receiving a lower return on their effort on a difficult order as a potential loss. This effect is more likely to be salient with transparency, where workers have the required information to frame the loss at the outset. In contrast, our results in subsubsection 3.5.2 suggest that with transparency, workers' rejection rates and WTP are not significantly different across the intuitiveness levels, which rules out loss aversion as a possible explanation.

3.5.3 Analysis and Results: Study 3

In Study 3, we focus on the impact of a change in the platform's pay algorithm from intuitive to non-intuitive. Recall that participants were required to fulfill the first two orders offered to them. A random subset of participants under each transparency level experienced a switch to the non-intuitive algorithm after fulfilling the first order. Their WTP was elicited for the third order.

Our empirical approach to studying the effect of change involves modeling workers' willingness to work for the platform as a function of $\textit{Change}_i$, which equals 1 if the participant observed a change in the algorithm, while controlling for the variable $\textit{Transparent}_i$ and the order characteristics. Our regression model for $\textit{Engagement}_i \in \{\textit{Reject}_i, \textit{WTP}_i\}$ is

$$\textit{Engagement}_i = \textit{Constant} + \lambda_1 \textit{Transparent}_i + \lambda_2 \textit{Change}_i + \lambda_3 \textit{Difficult}_{1i} + \lambda_4 \textit{Difficult}_{2i} + \epsilon_i, \tag{3.6}$$

whereas for perceptions, we use

$$\begin{aligned}\textit{Perception}_i = \textit{Constant} + \mu_1 \textit{Transparent}_i + \mu_2 \textit{Change}_i + \mu_3 \textit{Difficult}_{1i} + \mu_4 \textit{Difficult}_{2i} \\ + \mu_5 \textit{Easy}_{3i} + \mu_6 \textit{Difficult}_{3i} + \epsilon_i.\end{aligned} \tag{3.7}$$

Switch to a non-intuitive algorithm hurts worker engagement on a transparent platform:

The results of these analyses are reported in Table 3.10. From the coefficients on *Change* in columns (1) and (2), we observe that workers who experience a switch to a non-intuitive algorithm directionally have a higher propensity to reject work and are willing to pay a lower participation cost to work for the platform, but these effects are not statistically significant. However, as evident from columns (3)-(8), the algorithm change results in significantly poorer perceptions of the platform particularly around trust, fairness, favorability, and work-attractiveness.

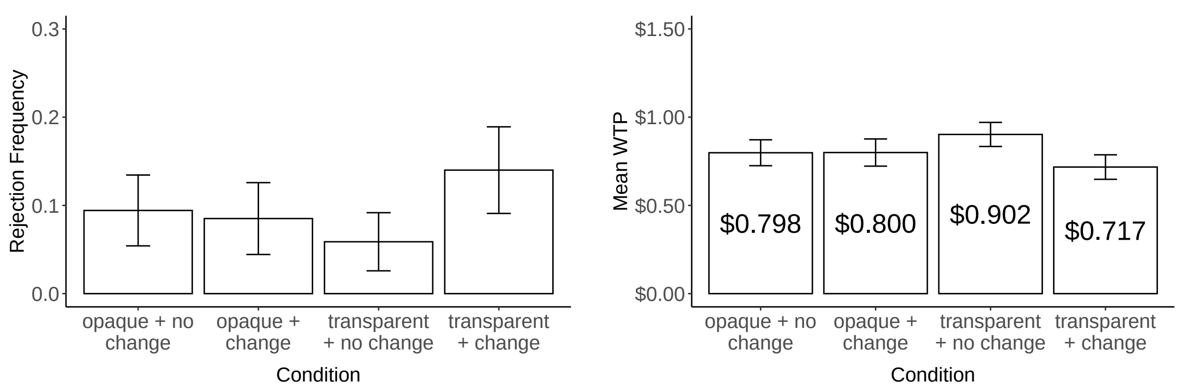
Next, we examine how transparency affects workers' engagement after the algorithm change. Visualizations of the rejection frequency and the mean WTP under different conditions of change

Table 3.10: Effect of change, Study 3

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Transparent	0.008 (0.042)	0.015 (0.072)	0.171 (0.171)	0.742*** (0.217)	0.557** (0.215)	0.340* (0.173)	0.331* (0.198)	0.540** (0.225)
Change	0.035 (0.042)	-0.095 (0.072)	-0.333* (0.171)	-0.312 (0.218)	-0.435** (0.216)	-0.270 (0.173)	-0.412** (0.199)	-0.519** (0.225)
Difficult_1	0.016 (0.042)	0.048 (0.073)	0.251 (0.173)	0.228 (0.219)	0.120 (0.218)	0.154 (0.175)	0.127 (0.200)	0.171 (0.227)
Difficult_2	0.005 (0.042)	-0.077 (0.073)	-0.251 (0.173)	-0.414* (0.219)	-0.574*** (0.217)	-0.116 (0.174)	-0.416** (0.200)	-0.412* (0.226)
Easy_3			0.654*** (0.207)	0.354 (0.263)	0.475* (0.261)	0.236 (0.209)	0.419* (0.240)	0.360 (0.272)
Difficult_3			0.328 (0.207)	0.380 (0.263)	0.327 (0.261)	0.223 (0.210)	0.314 (0.240)	0.307 (0.272)
Constant	0.063 (0.044)	0.860*** (0.077)	4.827*** (0.208)	4.128*** (0.264)	4.711*** (0.261)	5.113*** (0.210)	4.692*** (0.241)	4.351*** (0.272)
Observations	201	201	201	201	201	201	201	201

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

are provided in Figure 3.3a and Figure 3.3b respectively. These figures illustrate that the algorithm change does not affect workers' likelihood of rejection or their WTP when the platform is opaque. Conversely, when the platform is transparent, workers' rejection frequency tends to rise and their WTP drops under the newly-implemented non-intuitive algorithm.



(a) Rejection frequency per condition

(b) Mean WTP per condition

Figure 3.3: Study 3 Rejection frequency and Mean WTP across conditions of algorithm change. Bars indicate standard errors

For a formal analysis of these visual observations, we add the interaction of $Change_i$ and $Transparent_i$ to our regression models. Results of these analyses reported in Table 3.11 provide statistical support for the insights from Figure 3.3. That is, when the platform is opaque, the change does not have a significant impact on workers' likelihood of rejection or WTP, as indicated by columns (1)-(2). In contrast, when the platform is transparent, the algorithm change results in a directionally higher likelihood of rejection and a marginally lower willingness to work for the platform ($p < 0.1$), which is verified by using a linear hypothesis test on the sum of coefficients on *Change* and *Transparent* x *Change* (demonstrated in the second-to-last row of Table 3.11). Interestingly, columns (3)-(8) highlight that workers have significantly negative perceptions of an opaque platform after the change. Being transparent neutralizes this effect, which is confirmed by the results of linear hypothesis tests demonstrated in the second-to-last row of the table.

In Appendix subsection B.2.1, we unpack the drivers for the drop in workers' willingness to work for a transparent platform and for the decline in workers' perceptions of an opaque platform following a change from an intuitive to a non-intuitive algorithm. For this purpose, we divide the *Change* variable further into two categories to capture a worker's experience with the change. Workers who are assigned a difficult second order (OC3 or OC4) undergo a decrease in financial return on their effort, since the newly introduced non-intuitive algorithm pays less for such orders. In contrast, workers who are assigned an easy second order (OC1 or OC2) undergo an increase in financial return on their effort. Results of this analysis (presented in Appendix subsection B.2.1 and omitted here for brevity) conclude that the drop in workers' willingness to work for a transparent platform and the decline in workers' perceptions of an opaque platform following the algorithm change can be attributed to workers who experience a decrease in return on their effort due to the change.

Our findings point to a critical trade-off that transparency poses when platforms consider a change from an intuitive algorithm to a non-intuitive one. With transparency, a switch to a non-intuitive algorithm results in weaker worker engagement, but it does not hurt workers' perceptions about the platform since it helps them make informed engagement decisions for themselves after the change, which is likely to be beneficial over the long run. In contrast, being opaque helps a platform reduce the short-term negative impacts of an algorithm switch on worker engagement, but ultimately, workers' perceptions of the platform are hurt after such an experience.

Table 3.11: Effect of transparency in managing engagement under change, Study 3

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Transparent	-0.038 (0.058)	0.103 (0.101)	-0.117 (0.238)	0.417 (0.302)	0.204 (0.299)	0.001 (0.239)	0.011 (0.276)	0.206 (0.312)
Change	-0.013 (0.060)	-0.004 (0.103)	-0.636*** (0.244)	-0.654** (0.311)	-0.808*** (0.308)	-0.628** (0.246)	-0.750*** (0.283)	-0.872*** (0.321)
Transparent × Change	0.096 (0.084)	-0.181 (0.146)	0.597* (0.345)	0.675 (0.438)	0.734* (0.434)	0.705** (0.347)	0.666* (0.400)	0.696 (0.453)
Difficult_1	0.022 (0.042)	0.037 (0.074)	0.289* (0.173)	0.271 (0.220)	0.167 (0.218)	0.198 (0.175)	0.168 (0.201)	0.215 (0.228)
Difficult_2	0.006 (0.042)	-0.078 (0.073)	-0.247 (0.172)	-0.410* (0.218)	-0.570*** (0.216)	-0.111 (0.173)	-0.412** (0.199)	-0.407* (0.226)
Easy_3			0.682*** (0.207)	0.386 (0.263)	0.509* (0.260)	0.269 (0.208)	0.450* (0.240)	0.393 (0.272)
Difficult_3			0.356* (0.207)	0.412 (0.263)	0.361 (0.261)	0.256 (0.208)	0.345 (0.240)	0.339 (0.272)
Constant	0.083* (0.048)	0.822*** (0.083)	4.934*** (0.216)	4.249*** (0.274)	4.842*** (0.271)	5.239*** (0.217)	4.811*** (0.250)	4.476*** (0.283)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Change + (Transparent × Change)	0.083 (0.059)	-0.185* (0.102)	-0.039 (0.241)	0.020 (0.306)	-0.074 (0.303)	0.077 (0.242)	-0.085 (0.279)	-0.176 (0.316)
Transparent + (Transparent × Change)	0.058 (0.060)	-0.078 (0.105)	0.481* (0.247)	1.092*** (0.314)	0.938*** (0.311)	0.706*** (0.249)	0.676** (0.286)	0.902*** (0.325)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Transparency does not hurt worker engagement and helps to boost worker perceptions compared to opacity:

Should a platform that might change its algorithm in the future nevertheless commit to transparency? To answer this question, it is essential to compare workers' behavior and perceptions between the two transparency conditions. In Table 3.11, the coefficient of *Transparent* captures the comparison of the two transparency conditions when workers do not experience an algorithm change, while the sum of *Transparent* and *Change* x *Transparent* (which are demonstrated in the last row of the table) captures that comparison when workers experience an algorithm change. As evident from columns (1) and (2), transparency does not hurt workers' engagement, irrespective of an algorithm change. Furthermore, from columns (3)-(8), we observe that transparency helps to boost perceptions particularly after a non-intuitive algorithm is implemented. In Appendix subsection B.2.2, we examine the role of transparency in managing workers' perceptions of the change. Results of this analysis conclude that transparency also helps in neutralizing perceptions about the inappropriateness of the non-intuitive algorithm that we observe among workers who see a decrease in return on their effort on an opaque platform. Therefore, our results suggest that a platform will not be hurt by committing to transparency and may actually benefit from it over the long run by motivating positive perceptions of workers.

Robustness: As before, Appendix section B.3 shows consistent results after controlling for risk aversion and participant demographics.

3.6 Concluding Remarks

On-demand service platforms have been experimenting with different kinds of algorithms to compensate workers. While few platforms have continued using algorithms that are intuitive to workers such as those that are commission- or effort-based, others have transitioned to using algorithms that incorporate a variety of factors potentially exogenous to the task, under which workers find it difficult to rationalize their pay. The lack of transparency on how much the different components of work are paid for exacerbates their difficulty. Despite the anecdotal evidence on workers' frustration with these algorithmic features, it is not clear at the outset whether these reactions reflect a systematic effect on workers' decisions to work for the platform and their perceptions, and what features of the algorithm are responsible for workers' negative reactions. In this paper, we conduct incentivized online experiments with human subjects to examine how the pay algorithm's intuitiveness to workers and its transparency affect their willingness to work for a platform and perceptions of the platform. We highlight three sets of insights.

First, neither the intuitiveness of the pay algorithm nor its transparency has a significant influence on the decisions of workers considering joining the platform for the first time. However, transparency into the algorithm helps to improve perceptions about the platform, irrespective of the algorithm's intuitiveness to workers, which can be valuable for the platform in the long run.

Second, for workers who have some experience of working for the platform and being paid by its algorithm, the intuitiveness of the algorithm and its transparency are influential in sustaining workers' engagement with the platform. We find that transparency is particularly valuable in sustaining workers' engagement when the algorithm does not conform to workers' intuition; transparency in this case helps to reduce workers' rejection rates of the orders offered by the platform and increases the participation cost they are willing to pay to work for the platform. Moreover, we find that this value created by transparency is sufficient to overcome workers' lower willingness to work under the non-intuitive algorithm, leading the platform to achieve comparable worker engagement levels to that under an intuitive algorithm. This effectiveness of transparency is achieved largely through the instrumental role it plays in managing workers' experiences with unfavorable pay outcomes under the non-intuitive algorithm. Thus, our results highlight that keeping non-intuitive algorithms opaque, as several platforms have done in practice, can systematically harm workers' engagement with the platform. Our results suggest that platforms can operationalize a non-intuitive algorithm by providing workers with a clear breakdown of how their algorithm compensates different components of the task, which prepares them for the future outcomes and mitigates the consequences of their disappointment. Transparency tends to be beneficial in managing workers' perceptions as well, regardless of algorithm intuitiveness.

Third, we find that a change in algorithm from intuitive to non-intuitive implemented by a transparent platform hurts workers' engagement on the platform, but we observe no such effect on an opaque platform. Despite transparency's short-term negative impact, committing to transparency can ultimately be beneficial for the platform in the long run for two reasons: (1) Workers have significantly poor perceptions of an opaque platform after the change, and transparency helps to neutralize this effect. (2) The level of worker engagement with transparency is not dominated by that achieved by opacity, even after an algorithm change.

Our work in this paper is focused on understanding how two specific features of a pay algorithm – its intuitiveness to workers and its transparency – affect workers' engagement with the platform. Our modeling of intuitiveness is based on whether the compensation for each task correlates with effort. Future work can investigate the effect of other features of the pay algorithm that can contribute to an algorithm's intuitiveness to workers, such as random bonuses that may make pay less predictable, or its structural complexity. There can also be practical value in considering a moderate level of transparency, wherein the platform reveals which factors weigh more than others, instead of revealing their values explicitly.

Ours is, to our knowledge, the first attempt to explore and underscore the effects that features of a platform's pay algorithm can have on workers' economic decisions such as their willingness to work for the platform and workers' perceptions of the platform. We hope that our work motivates further studies with the objective of understanding ways to improve workers' experiences on on-demand service platforms.

CHAPTER 4
PLATFORM COMMISSION AND ITS TRANSPARENCY ON ON-DEMAND SERVICE PLATFORMS

4.1 Introduction

In recent years, on-demand service platforms such ridesharing, grocery-delivery, courier-delivery, and food-delivery platforms have come to revolutionize how certain services get delivered to customers. Platforms such as Uber, Lyft, Bolt, Grab, Ola, and Instacart adopt the role of an intermediary that connects service-seeking customers to service-providing agents (workers). In this role, platforms make several critical decisions, one of which pertains to the commission to be charged to workers on a service request completed on the platform. Prevailing literature on workers' participation decisions on a platform assumes that workers only consider their own economic outcomes in making these decisions. However, the platform's commission, which is the difference between the price it charges the customer and its payment to the worker who fulfills the service request, can influence workers' evaluation of the prospect of working for the platform. Thus, workers' participation decisions may be affected by their payoffs *relative* to the platform. Examining how a platform's practices pertaining to the commission that it charges workers influence workers' behavior is the focus of this paper.

Platforms have been experimenting with how they determine the commission that workers pay on the service requests they complete through the platform. Early in their conception, many platforms used a fixed commission model, where the price on a service request is determined such that the worker fulfilling it is paid based on effort-based factors such as time and distance, and the platform earns a fixed percentage commission on the price. Several platforms such as Ola (Ola 2023), Bolt (Bolt 2021), Gojek (Yufeng 2022), DiDi Australia (DiDi 2021), and 99Taxi (Schieber 2015), continue to operate under this model. Subsequently, however, some platforms decoupled the customer price from workers' earnings (Allyn 2021), such that the platform's commission not consistent across service instances (Cox 2019). Under this model, platforms compensate workers for their effort on the task, but utilize several additional factors both endogenous and exogenous to the service task to determine the price. This leads to the platform's commission being variable across service instances. For instance, under Uber's and Lyft's variable commission structures, drivers are paid a consistent amount per unit time and distance on a trip (Kerr 2022; Lyft 2022), whereas the price is dependent on several additional factors (Uber Marketplace 2023; Lyft 2023)—that do not influence what the worker earns, such as riders' willingness to pay (Newcomer 2017; Martin 2019).

This change has marked a significant shift in workers' experience of working with these platforms. Under the fixed commission model, workers fully understand the relationship between the price paid by the customer and their share in the revenue. In contrast, they are less informed about this relationship when the platform's commission is variable. These new practices have led to suspicion and distrust about certain platforms among workers. In particular, workers are concerned whether they receive a fair share of the value created by the platform. Platforms argue that this model helps improve customers' experience through better prices. Furthermore, by keeping a higher commission through charging higher prices in certain instances can help the platform offset the lower revenue realized when it keeps a lower commission through charging lower prices (Uber Marketplace 2023). Finally, platforms argue that workers are better off under the variable commission model as they realize more earning opportunities through the platform (Uber Marketplace 2023).

In addition to whether the commission is fixed or variable, workers' knowledge of the platform's commission is also influenced by its transparency to workers. It has been observed anecdotally that when platforms have implemented a fixed commission model, they have been transparent about the percentage commission that they charge workers. For instance, platforms such as Ola (Ola 2023), Bolt (Bolt 2021), Gojek (Yufeng 2022), DiDi Australia (DiDi 2021), and 99Taxi (Schieber 2015), have made the percentage commission that they keep, public. In contrast, under the variable commission model, platforms have experimented with workers' visibility of their commission on individual service requests. For instance, both Uber and Lyft earlier adopted full transparency under their variable commission models, wherein drivers could observe the customer price and hence the platform's commission on each trip. However, platforms faced significant backlash from drivers when they realized that the platforms were securing a large portion of the customer price on some trips (Siddiqui 2021b). In response, platforms have experimented with reducing the transparency of their commission to drivers. For instance, Uber experimented with withdrawing drivers' visibility of the customer price (Zhou 2022). Concurrently, Lyft experimented with an intermediate level of transparency, wherein a driver could access only aggregate information about the price on their trips (Gordon 2019). Platforms have argued that their opacity on commission is motivated by the objective to help workers focus on their own earnings (Gordon 2019).

Anecdotal evidence, however, suggests that the lack of transparency has not been received well by drivers either. Drivers have expressed suspicion that by concealing information on price from them, the platform keeps a large portion of the price paid by the customer (Gordon 2019). Under such opacity, drivers also find it more difficult to make an informed decision about their participation on the platform, by making it difficult for them to evaluate whether they would earn a fair share of the transaction. Concurrently, realizing workers' frustrations, new platforms based on lower commission and transparent commission policies have been emerging and attracting workers[1](Mansur 2022).

Overall, these observations from practice suggest that workers (i) may resist a variable commission model where the platform's commission in some service instances is larger than in others, and (ii) may be frustrated by a platform's attempts to make it more difficult for workers to observe the platform's commission. However, several things about workers' attitudes towards platform commission remain unclear from the anecdotally reported reactions of workers. Firstly, it remains to be systematically understood how the platform's commission level influences workers' decision to work for the platform. Secondly, how does this worker behavior influence the commission that

[1]https://nammayatri.in/

platform can charge workers under the fixed and variable commission models? Thirdly, it is not clear at the outset if and how worker participation and their perceptions of the platform vary across the fixed and variable commission models. For instance, if workers are averse to variability in platform commission, is the platform constrained to keeping a lower commission on average than in the fixed commission model? Finally, the effect of transparency about the platform's commission under the variable commission model on worker behavior is not well understood. Therefore, a careful analysis of workers' value for platform's commission and its transparency is required. In this paper, we experimentally study how these two features associated with workers' relative earnings influence their participation on the platform and their perceptions of the platform.

Making decisions pertaining to its commission is not trivial from the platform's perspective as they involve significant tradeoffs. Research on fairness preferences suggests that people are sensitive to how their outcomes *compare* with those of others. Moreover, fairness concerns invoked by such a comparison can determine how people reciprocate; people can resist outcomes that they deem unfavorable to them in a relative sense (Fehr and Gächter 2000). In our context, this would suggest that in general, workers find higher platform commission unfair and may resist participating under such conditions. However, prior literature also suggests that there is heterogeneity in fairness preferences across individuals (Falk et al. 2006); some people may be more sensitive to relative payoffs than others. To that end, it is possible that at an aggregate level, workers may not display significant resistance towards higher platform commission. Secondly, a platform's choice between the fixed and variable commission models could involve a potential trade-off between efficiency and fairness concerns of workers. On one hand, having more flexibility in adjusting the price (and hence, the commission) can help the platform attract more customers through better prices and potentially generate greater revenue. However, the realization of these benefits depends on worker behavior. When the platform's commission is variable, instances where the platform commission is lower can serve as a reference and lead workers to deem higher commission unfair, which can hurt worker participation. Therefore, the potential benefits of the variable commission model are not guaranteed to materialize. Furthermore, the efficacy of opacity in operationalizing the variable commission model is not straightforward. On one hand, the opacity of platform commission can reduce workers' sensitivity to the platform's share of revenue on individual service requests and improve worker participation on the platform. However, prior literature has shown that transparency helps to boost trust and credibility (Bernstein 2017; Core 2001; Healy and Palepu 2001; Leuz and Wysocki 2016; Levitin 2013; Ullmann 1985). To that end, the lack of transparency on the platform commission can increase worker distrust and reduce their participation on the platform. Therefore, a careful analysis of worker behavior in this context is warranted.

Given these considerations, we aim to answer the following research questions: (1) How does the platform's commission level under the fixed and variable commission models influence workers' participation decisions on the platform? (2) How do workers' participation decisions and perceptions of the platform compare across the fixed and variable commission models? and (3) How does the transparency of a platform's commission under the variable commission model influence workers' participation decisions on the platform and their perceptions of the platform?

To answer these questions, we design incentivized experiments to be conducted online on Prolific using a setting that involves three players—the customer, the worker, and the platform who acts as an intermediary between the two. The customer is computer simulated, while human participants are randomly assigned to assume the role of either the platform or the worker and are paired throughout the experiment. The pairs are randomly assigned to the fixed commission or the variable commission treatment. In both treatments, the platform makes a pricing decision that influences the likelihood that the customer—with a stochastic maximum willingness to pay, places a service request. In the fixed commission treatment, the platform commits upfront to one price for all experimental periods, whereas in the variable commission treatment, the platform can set different prices for different distributions of customers' willingness to pay that it may realize. The platform pays the worker a wage rate that is determined exogenously, and the difference between the platform's price and its payment to the worker is the commission it charges the worker. The worker decides upfront, the maximum platform commission that she is willing to pay to the platform. A customer places a request if and only if the platform's price is less than or equal to his

WTP. Further, the service request can be assigned to the worker if and only if the platform charges a commission on the task that is not greater than what the worker is willing to pay. We implement the variable commission treatment under two transparency conditions. That is, participant pairs assigned to the variable commission treatment are randomly assigned to one of two conditions. In the transparent condition, the worker can eventually observe the price charged by the platform on a service task, whereas under the opaque condition, this information is never revealed to the worker. At the end of the experiment, workers' perceptions of the platform and the risk preferences of all participants are elicited. In the next section, we discuss the related literature, and in section 4.3, we provide the details of our experimental design.

4.2 Related Literature

Our work in this paper contributes to three streams of literature. Firstly, this paper is related to a growing body of Operations Management literature on on-demand service platforms. There has been extensive research that studies platforms' decisions around pricing and workers' wages. Some papers evaluate a platform's fixed commission policy (Cachon et al. 2017; Bimpikis et al. 2019; Guda and Subramanian 2019; Besbes et al. 2021; Bimpikis et al. 2019; Hu et al. 2022; Bai et al. 2019), while several researchers have also studied settings where the price and wage can be determined independently by the platform (Cachon et al. 2017; Taylor 2018; Gurvich et al. 2019; Hu and Zhou 2020; Bimpikis et al. 2019; Bai et al. 2019). However, this body of literature assumes that workers make their labor supply decisions based only on their own economic outcomes. In contrast, this paper studies how worker behavior on the platform may be motivated by how much they earn on a service task *relative* to the platform.

Secondly, our work connects with literature on the role of fairness concerns in social and economic interactions. In particular, prior literature has shown that individuals resist outcomes that they deem unfair. One piece of supporting evidence for this behavior is found in the widely studied and replicated ultimatum game (Güth et al. 1982). In this game, an Allocator is asked to divide an amount of money between himself and a Recipient. If the split is accepted by the Recipient, the allocation is executed, whereas if it is rejected, both players receive nothing. Normative theory would predict that the Allocator should offer the Recipient the smallest portion possible, and the Recipient should accept it given that her outside option is zero. The experimental data, however, is inconsistent with both hypotheses; anticipating that low offers are likely to be rejected, Allocators offer a significantly higher amount to the Recipient than the lowest possible amount, and Recipients reject low offers whenever they do encounter them (Thaler 1988). Follow up work has built a theory of reciprocity, which suggests that individuals reward kind actions of others and punish unkind ones (Falk and Fischbacher 2006). Some researchers have studied the role of such fairness concerns and reciprocity in labor markets. Akerlof and Yellen (1990) put forth the fair wage-effort hypothesis, according to which, workers proportionately withdraw effort as their actual wage falls short of their fair wage. In an experimental setting, Falk et al. (2006) find that workers' reservation wages are influenced by the presence or absence of a minimum wage law. In particular, under the minimum wage law, workers perceive receiving a minimum wage offer as rather unfair and thus have reservation wages that are above the minimum wage. This leads firms to have to pay much more than the minimum wage. In contrast to the aforementioned literature, our study focuses on the context of on-demand service platforms. Furthermore, we examine the role of the procedures (i.e., fixed or variable commission) that determine the distribution of payoffs between the worker and the platform, in influencing workers' participation and their perceptions.

Finally, our paper is related to work on the role of transparency in Operations Management. Work in this domain examines transparency as an operational lever on the consumer-side and the supply-side. Prior work has examined the role of transparency into the service process for signaling service provider effort (Buell and Norton 2011; Buell et al. 2017), or sharing progress in the product delivery process (Bray 2020), or position in a queue (Buell 2021). Transparency is also extensively studied in the domain of supply chains. Research has examined how transparency into internal and external initiatives towards social and environmental responsibility (Buell and Kalkanci 2021) affects consumer perceptions and purchase behavior. Lately, research on transparency has expanded into new operational settings such as governmental operations (Buell et al. 2021) and crowdfunding platforms (Mejia et al. 2019). In these contexts, transparency serves as a lever in managing relations with residents and donors, respectively. In contrast to the extensive work on the consumer-side, research investigating the effect of operational transparency on the supply-side is relatively scarce. Researchers have studied the effect of transparency into an organization's previous purchases on employees' procurement decisions (Beer et al. 2021). In the context of ridesharing platforms, Mejia and Parker (2021) examine the effect of transparency about riders' details on drivers' ride acceptance and cancellation decisions. In Buell et al. (2017), authors find that providing service providers, visibility of the customers that they are serving leads to higher service quality and efficiency. Our paper adds to this body of work by considering how visibility of a platform's commission on a service request, when the platform commission may not be consistent, influences workers' participation decisions and their perceptions of the platform.

4.3 Experimental Design

In our experimental setup, we capture the platform's environment relevant to our research questions using a computerized setting. There are three players in the experiment—the customer, the worker, and the platform who acts as an intermediary between the two. The roles of the platform and the worker are played by human participants, while the customer is computer simulated. Human participants are randomly assigned to assume the role of either the platform or the worker and are paired throughout the experiment. Facing a customer in each period whose maximum Willingness to Pay (WTP) for the service is random, the platform is responsible for setting the price. The price influences the probability that the customer places a service request. The platform pays the worker a wage rate that is determined exogenously. The difference between the platform's price and its payment to the worker is the commission that the platform charges the worker. The worker decides upfront, the maximum platform commission that she is willing to pay to the platform. A customer places a request if and only if the platform's price is less than or equal to his WTP. A service request can be assigned to the worker if and only if the platform charges a commission that is not greater than what the worker is willing to pay. In two treatments, we manipulate the kind of pricing decisions that the platform can make; the platform is either asked to make a pricing decision in a setting where its commission is consistent, or in a setting where it can charge a variable commission. To explore the effect of transparency under the treatment with variable commission, we implement the corresponding treatment under two transparency conditions. Under the transparent condition, the worker can eventually observe the platform's commission on a service task, whereas under the opaque condition, this information is never revealed to the worker. At the end of the experiment, workers' perceptions of the platform, and all participants risk preferences are elicited. In the next few subsections, we provide more details of the experimental design.

4.3.1 Platform and Worker Decisions

In our experiment, we mimic the setting of a ridesharing platform. This is because our research questions and motivation identify closest with this setting. At the beginning of period t of the experiment, the platform faces a customer—simulated by the computer, whose WTP, V_t, for the ride is uniformly distributed in $[\underline{V}, \overline{V}]$ for all t. The range of V_t is known to the worker but the distribution is unknown. The platform determines the price, p_t, under uncertainty about V_t. The customer places a service request if and only if the platform's price, p_t, is less than or equal to the customer's WTP. From the price paid by the customer, the platform is committed to paying the worker a wage, while the rest is charged to the worker as commission on the service task. The worker decides the maximum commission, i.e., the difference between the platform's price and the worker's wage, that she is willing to pay on a service task, under uncertainty about p_t. A service request can be assigned to the worker if and only if the platform's commission is not greater than the maximum commission that the worker is willing to pay.

4.3.2 Service Tasks and Wage Rate

Service tasks in our experiment mimic those on a ridesharing platform, captured in a computerized environment. A task is composed of several subtasks—each involving a traffic situation and modeled using slider tasks (Gill and Prowse 2011) that are widely used in experimental studies with real effort. Workers encounter several traffic situations sequentially and are asked to take appropriate action towards each of them. Workers are shown a traffic situation for a duration of 30 seconds and lose a small amount for each traffic situation that they miss or respond incorrectly to. To reduce the variability in the environment that workers are exposed to, we assume that the platform receives only one type of service request. To that end, the number of subtasks (i.e., traffic situations) in a service request received in period t, N_t, is such that $N_t = N$ for all t.

To restrict our attention to the platform's commission, we assume that the platform offers the worker a fixed and exogenously specified wage rate, w, on each subtask (i.e., traffic situation) in a service task. This is also consistent with the fact that platforms continued to determine workers' compensation on a service task using effort-based factors such as time and distance, even as they transitioned from keeping a fixed commission to keeping a variable commission (Uber Blog 2021). We assume that customers are aware that it costs the platform at least $(w \times N)$ to provide the service and are therefore willing to pay at least $(w \times N)$. To that end, we assume $\underline{V} > (w \times N)$.

4.3.3 Payoffs

The payoffs of the platform and the worker in a period depend critically on the platform's price. At the start of each period, the platform is endowed with an amount E_p, while no such amount is endowed to the worker. We adapt this experimental feature from Kraft et al. (2018) to reflect the relatively disadvantaged position and lower opportunity cost of the worker. In the case that the customer arriving in a period does not get served, the worker earns nothing in that period and platform earns nothing over its initial endowment. If, however, the customer arriving in a period is served by the worker, then the worker earns $(w \times N)$, while the platform earns the commission, $p_t - (w \times N)$, over its initial endowment. To maintain that the platform's final wealth is larger than that of the worker, we select the platform's initial endowment, E_p, such that $E_p > 2(w \times N) - \underline{V}$. We set parameters in the experiment such that if a service request is completed, the worker's payoff from the transaction is higher than that of the platform. This reflects the reality that the platform's commission on a service request is unlikely to exceed 50% of the price. Therefore, we assume that

$\overline{V} < 2(w \times N)$.

4.3.4 Experimental Treatments and Conditions

Since the wage offered to the worker is held fixed, whether the platform's commission is consistent or variable across the service instances is only influenced by how the platform determines the price in our experiment. We design two treatments between-subjects: the *Fixed Commission* treatment and the *Variable Commission* treatment. In each of these treatments, the platform makes a pricing decision, which influences the likelihood that the customer places a service request and whether the worker accepts it. Further, we implement the Variable Commission treatment under two conditions; under the transparent condition, the worker can observe the price set by the platform, whereas under the opaque condition, the worker cannot observe the price set by the platform.

Fixed Commission Treatment

Under fixed commission, the platform commits to keeping a commission that remains consistent across the experimental periods. In our experimental setup, this implies that the platform commits to a single price. Therefore, in this treatment, the participant playing the role of the platform is asked to decide a price, $p_t = p \in [\underline{V}, \overline{V}]$ that would apply to each period t.

The worker states the maximum commission, $WTP^w \in [\underline{V} - (w \times N), \overline{V} - (w \times N)]$, that she is willing to pay to accept and fulfill a service request. The worker is informed that V_t is in the range $[\underline{V}, \overline{V}]$, but is uninformed about its probability distribution. This this reduces the chance that worker participants make decisions based on the probability of receiving earning opportunities resulting from a price.

The platform player then proceeds to the post-experimental section, and in the rest of the experiment, the worker is the only active participant. The platform price $p_t = p$ is revealed to the worker. Then, in each period t, $V_t = v_t$ is drawn from the uniform distribution $U[\underline{V}, \overline{V}]$, and a service request is completed if and only if $p_t = p \leq v_t$ and $p - (w \times N) \leq WTP^w$. The payoffs of the platform and the worker in the period then follow as described in subsection 4.3.3. At the end of each period, the worker is shown a summary of his own and the platform's payoffs for the period. At the end of all experimental periods, the worker proceeds to the post-experimental section.

Variable Commission Treatment

Under variable commission, the platform is not bound to charge workers a fixed commission; it can vary the commission it charges across service instances. In doing so, the platform can utilize certain factors to determine the price that are independent of those that determine the worker's wage. Consistently, in this treatment, while the worker is compensated using a fixed wage rate per unit effort, the platform can make a more granular pricing decision for the customer. Specifically, the platform can determine different prices for different segments of customers' WTP.

The treatment evolves as follows. At the beginning of the experiment, the participant playing the role of the platform knows that the probability distribution of V_t is $U[\underline{V}, \overline{V}]$. At the beginning of each period, the platform receives more information about the customer's WTP. In particular, the platform either observes that $V_t \sim V_{t,l}$ or $V_t \sim V_{t,h}$ at the beginning of a period, where $V_{t,l} \sim U[\underline{V}, (\underline{V} + \overline{V})/2]$ and $V_{t,h} \sim U[(\underline{V} + \overline{V})/2, \overline{V}]$. The platform decides prices, $p_{t,l}$ and $p_{t,h}$, conditional on $V_t \sim V_{t,l}$ and $V_t \sim V_{t,h}$, respectively. To control for platform's learning over the experimental periods across the two treatments, the participant playing the role of the platform is informed at the beginning of the experiment that $V_t \sim V_{t,l}$ and $V_t \sim V_{t,h}$ are equally likely, and is asked to decide $p_{t,l}$ and $p_{t,h}$ at the beginning of the experiment. Moreover, to maintain that the worker is not aware of the information about the distribution of V_t possessed by the platform, we ask the platform participant to choose $p_{t,l}$ and $p_{t,h}$ in the range $[\underline{V}, \overline{V}]$.

The worker states the maximum commission, $WTP^w \in [\underline{V} - (w \times N), \overline{V} - (w \times N)]$, that she is willing to pay to accept and fulfill a service request, without knowing the platform's pricing decision. The worker is informed that V_t is in the range $[\underline{V}, \overline{V}]$, but is uninformed about its probability distribution. The worker knows that the platform can decide two different prices. Overall, this reduces the chance that worker participants make decisions based on the probability of receiving earning opportunities resulting from a price.

The platform player then proceeds to the post-experimental section, and in the rest of the experiment, the worker is the only active participant. Then, in each period t, $V_t \sim V_{t,l}$ or $V_t \sim V_{t,h}$ is realized with equal chance, and v_t is drawn from the realized distribution V_t. If $V_t \sim V_{t,l}$, then $p_t = p_{t,l}$ applies, whereas if $V_t \sim V_{t,h}$, then $p_t = p_{t,h}$ applies.

We design the Variable Commission Treatment to be conducted under two conditions of transparency. Under the *transparent* condition, the worker observes p_t at the beginning of each period. A service request is completed if and only if $p_t \leq v_t$ and $p_t - (w \times N) \leq WTP^w$. The payoffs of the platform and the worker in a period then follow as described in subsection 4.3.3. At the end of each period, the worker is shown a summary of his own and the platform's payoffs for the period. At the end of all experimental periods, the worker proceeds to the post-experimental section.

Under the *opaque* condition, the worker never observes p_t. A service request is completed if and only if $p_t \leq v_t$ and $p_t - (w \times N) \leq WTP^w$. The payoffs of the platform and the worker in a period follow as described in subsection 4.3.3. At the end of each period, the worker is shown a summary of his own payoff for the period. At the end of all experimental periods, the worker proceeds to the post-experimental section.

4.3.5 Post-experimental Section

Following the main experiment, participants who play the role of the worker are given a questionnaire that includes questions about their perceptions about the platform. Specifically, we ask participants to rate their perceptions regarding trust, sincerity, fairness, and favorability towards the platform, their perception of the accuracy of information shared by the platform, and the attractiveness of the platform as an employer on a Likert scale.

In the post-experimental section, we also elicit the risk preferences of all participants. These are measured with the widely used multiple price list method (Holt and Laury 2002). Participants earn a small bonus based on the outcome of the risk preference elicitation task over their earnings from the experiment. Finally, we ask participants to respond to a demographic survey that includes questions about their age, gender, education, and income.

4.3.6 Sequence of Experimental Events

Participants on Prolific are first shown preliminary instructions about the experiment, followed by the consent form and detailed instructions. Participants are required to answer the questions of a comprehension quiz correctly to proceed to the main experimental session. Participants are randomly assigned to the role of either a worker or a platform in pairs. They are further assigned to one of the two treatments. Under the variable commission treatment, pairs are randomly assigned to one of the two transparency conditions. The main experimental session is followed by the post-experimental section.

Appendices

APPENDIX A

SUPPLEMENTAL MATERIALS FOR CHAPTER 2

A.1 Proofs

Preliminaries To simplify the presentation of the proofs, and without loss of generality, we redefine parameters in their normalized form, i.e., let $d_1 := d_1/n$, $d_2 := d_2/n$, $d_3 := d_3/n$, $r_1 := r_1/p$, and $r_2 := r_2/p$. Consequently, $D_1 := D_1/n \sim U[0,1]$, $D_2 := D_2/n \sim U[0,1]$, and $D_3 := D_3/n \sim U[0,1]$. Next, we state the expected earnings from staying and moving for drivers under each of the three information-sharing mechanisms—that we will refer to throughout the proofs.

First, consider surge information sharing. Under this mechanism, drivers observe the realized demand d_3 in Zone 3, but not the realized demand in Zones 1 or 2 (i.e., d_1 or d_2, respectively). For Zone 1 drivers, if the realized demand d_1 is less than or equal to the number of drivers staying in Zone 1, $(1+\gamma)(1-\theta_{1s}(d_3))$, the probability that a driver is allocated a customer is $d_1/[(1+\gamma)(1-\theta_{1s}(d_3))]$. If d_1 is greater than the number of drivers staying in Zone 1, a driver is assigned a customer with probability 1 and the surge multiplier is $d_1/[(1+\gamma)(1-\theta_{1s}(d_3))]$. Consequently, given d_1, the expected earnings over two stages for a driver in Zone 1 choosing to stay are $2d_1/[(1+\gamma)(1-\theta_{1s}(d_3)]$. Since drivers are uncertain about the realized demand d_1, the expected earnings for a Zone 1 driver from staying are given by

$$\int_0^1 \frac{2d_1}{(1+\gamma)(1-\theta_{1s}(d_3))} dd_1 = \frac{1}{(1+\gamma)(1-\theta_{1s}(d_3))}. \tag{A.1}$$

The expected earnings for Zone 1 drivers from moving can be calculated in a similar way and are given by

$$\frac{d_3}{(1+\gamma)\theta_{1s}(d_3) + (2-\gamma)\theta_{2s}(d_3)} - r_1. \tag{A.2}$$

Similarly, the expected earnings for a Zone 2 driver from staying are given by

$$\int_0^1 \frac{2d_2}{(2-\gamma)(1-\theta_{2s}(d_3))}dd_2 = \frac{1}{(2-\gamma)(1-\theta_{2s}(d_3))}, \tag{A.3}$$

and those from moving are given by

$$\frac{d_3}{(1+\gamma)\theta_{1s}(d_3)+(2-\gamma)\theta_{2s}(d_3)} - r_2. \tag{A.4}$$

Next, consider full information sharing. Under this mechanism, drivers observe the realized demand in Zones 1, 2, and 3 (i.e., d_1, d_2, and d_3, respectively). For the sake of brevity, and given the symmetry in the information available to drivers in Zones 1 and 2, we drop the dependence of θ_{1f} and θ_{2f} on the demand realizations; we use θ_{1f} instead of $\theta_{1f}(d_1, d_2, d_3)$ and θ_{2f} instead of $\theta_{2f}(d_1, d_2, d_3)$ throughout the equilibrium analysis of full information sharing. It follows similarly to surge information sharing that the expected earnings for Zone 1 drivers from staying are given by

$$\frac{2d_1}{(1+\gamma)(1-\theta_{1f})}, \tag{A.5}$$

and those from moving are given by

$$\frac{d_3}{(1+\gamma)\theta_{1f}+(2-\gamma)\theta_{2f}} - r_1. \tag{A.6}$$

Similarly, the expected earnings for Zone 2 drivers from staying are given by

$$\frac{2d_2}{(2-\gamma)(1-\theta_{2f})}, \tag{A.7}$$

and those from moving are given by

$$\frac{d_3}{(1+\gamma)\theta_{1f}+(2-\gamma)\theta_{2f}} - r_2. \tag{A.8}$$

Finally, consider local information sharing. Under this mechanism, Zone 1 drivers possess no information on the realized demand, while Zone 2 drivers observe the realized demand d_3 in Zone 3, but not the realized demand in Zones 1 or 2 (i.e., d_1 or d_2, respectively). It follows similarly as the analysis leading up to (Equation A.1) above that the expected earnings for a Zone 2 driver from staying are given by

$$\int_0^1 \frac{2d_2}{(2-\gamma)(1-\theta_{2\ell}(d_3))} dd_2 = \frac{1}{(2-\gamma)(1-\theta_{2\ell}(d_3))}, \tag{A.9}$$

and those from moving are given by

$$\frac{d_3}{(1+\gamma)\theta_{1\ell} + (2-\gamma)\theta_{2\ell}(d_3)} - r_2. \tag{A.10}$$

Similarly, for Zone 1 drivers, the expected earnings from staying are given by

$$\int_0^1 \frac{2d_1}{(1+\gamma)(1-\theta_{1\ell})} dd_1 = \frac{1}{(1+\gamma)(1-\theta_{1\ell})}, \tag{A.11}$$

while the additional uncertainty about the realized demand in Zone 3 implies that the expected earnings from moving are given by

$$E\left[\frac{d_3}{(1+\gamma)\theta_{1\ell} + (2-\gamma)\theta_{2\ell}(d_3)}\right] - r_1. \tag{A.12}$$

Proof of Proposition 1 First, we show that when $d_3 = 0$, a unique equilibrium exists in which $\theta^*_{1s}(d_3) = \theta^*_{2s}(d_3) = 0$. Note that if $d_3 = 0$, the expected earnings from moving given by (Equation A.2) and (Equation A.4) for drivers in Zones 1 and 2, respectively, are strictly negative because $r_1, r_2 > 0$. The expected earnings from staying given by (Equation A.1) and (Equation A.3), respectively, are strictly positive because $\theta^*_{1s}(d_3), \theta^*_{2s}(d_3) \in [0, 1)$ and $\gamma \in [0, 1]$. Since the expected earnings from staying dominate those from moving for drivers in Zones 1 and 2, it follows that $\theta^*_{1s}(d_3) = \theta^*_{2s}(d_3) = 0$ when $d_3 = 0$.

The rest of the proof of Proposition 1 focuses on the case where $d_3 > 0$.

(a) Zone 1 drivers do not move in equilibrium if and only if, given $\theta^*_{2s}(d_3)$, i.e., the equilibrium proportion of Zone 2 drivers that move, their expected earnings from staying are greater than or equal to those from moving for $\theta^*_{1s}(d_3) = 0$. It follows from (Equation A.1) and (Equation A.2) that Zone 1 drivers do not move in equilibrium if and only if

$$r_1 \geq \frac{d_3}{(2-\gamma)\theta^*_{2s}(d_3)} - \frac{1}{(1+\gamma)}. \tag{A.13}$$

At the equilibrium proportion $\theta^*_{2s}(d_3)$, by definition, Zone 2 drivers are indifferent between staying and moving, given $\theta^*_{1s}(d_3) = 0$. It follows from (Equation A.3) and (Equation A.4) that $\theta^*_{2s}(d_3)$ is obtained by solving

$$\frac{1}{(2-\gamma)(1-\theta^*_{2s}(d_3))} = \frac{d_3}{(2-\gamma)\theta^*_{2s}(d_3)} - r_2. \tag{A.14}$$

We obtain two solutions

$$\theta_{2s,1}(d_3) = \frac{1}{2}\left[\frac{1+d_3+r_2(2-\gamma)}{r_2(2-\gamma)}\right] - \frac{1}{2}\left[\frac{\sqrt{\left(1+r_2(2-\gamma)\right)^2 + 2d_3(1-r_2(2-\gamma)) + d_3^2}}{r_2(2-\gamma)}\right], \tag{A.15}$$

$$\theta_{2s,2}(d_3) = \frac{1}{2}\left[\frac{1+d_3+r_2(2-\gamma)}{r_2(2-\gamma)}\right] + \frac{1}{2}\left[\frac{\sqrt{\left(1+r_2(2-\gamma)\right)^2 + 2d_3(1-r_2(2-\gamma)) + d_3^2}}{r_2(2-\gamma)}\right]. \tag{A.16}$$

In expression (Equation A.16) for $\theta_{2s,2}(d_3)$, the term inside the square root can be rewritten as $(1+d_3)^2 + ((2-\gamma)r_2)^2 + 2(2-\gamma)r_2(1-d_3)$, which is strictly greater than $((2-\gamma)r_2)^2$ by $\gamma \in [0,1]$, $r_2 \in (0,1)$, and $d_3 \in (0,1]$. Then the second bracketed term on the right-hand side of the expression for $\theta_{2s,2}(d_3)$ is strictly greater than 1, which leads $\theta_{2s,2}(d_3)$ to be strictly greater than 1 by $r_2 \in (0,1)$, $\gamma \in [0,1]$, and $d_3 \in (0,1]$.

Consider the expression for $\theta_{2s,1}(d_3)$ in (Equation A.15). $\theta_{2s,1}(d_3) > 0$ because the square of the numerator of the second bracketed term on the right-hand side is less than $(1+(2-\gamma)r_2+d_3)^2$ because it can be rewritten as $(1+(2-\gamma)r_2+d_3)^2 - 4r_2d_3(2-\gamma)$, where $4r_2d_3(2-\gamma) > 0$ by $r_2 \in (0,1)$, $\gamma \in [0,1]$, and $d_3 \in (0,1]$. $\theta_{2s,1}(d_3) < 1$ because, by simple algebra, this is satisfied if and only if $(d_3+1-r_2(2-\gamma))^2 < (1+r_2(2-\gamma))^2 + 2d_3(1-r_2(2-\gamma)) + d_3^2$, which holds due to $r_2 \in (0,1)$ and $\gamma \in [0,1]$. Consequently, a unique internal solution $\theta^*_{2s}(d_3)$ exists, and is equal to $\theta_{2s,1}(d_3)$. Substituting $\theta^*_{2s}(d_3) = \theta_{2s,1}(d_3)$ in (Equation A.13), (Equation A.13) is equivalent to

$$r_1 \geq \overline{r}_s = \frac{d_3}{(2-\gamma)\theta_{2s,1}(d_3)} - \frac{1}{(1+\gamma)}. \tag{A.17}$$

In our original notation, $\overline{r}_s$ is equivalent to

$$\overline{r}_s = \frac{2pd_3r_2}{p\,(d_3+n) + (2-\gamma)nr_2 - np\sqrt{\frac{d_3^2}{n^2} + \frac{2d_3(p-(2-\gamma)r_2)}{np} + \frac{(p+(2-\gamma)r_2)^2}{p^2}}} - \frac{p}{1+\gamma}. \tag{A.18}$$

(b) Zone 2 drivers do not move in equilibrium if and only if, given $\theta^*_{1s}(d_3)$, i.e., the equilibrium proportion of Zone 1 drivers that move, their expected earnings from staying are greater than or equal to those from moving for $\theta^*_{2s}(d_3) = 0$. It follows from (Equation A.3) and (Equation A.4) that Zone 2 drivers do not move in equilibrium if and only if

$$r_2 \geq \frac{d_3}{(1+\gamma)\theta^*_{1s}(d_3)} - \frac{1}{(2-\gamma)}. \tag{A.19}$$

At the equilibrium proportion $\theta^*_{1s}(d_3)$, by definition, Zone 1 drivers are indifferent between staying and moving, given $\theta^*_{2s}(d_3) = 0$. It follows from (Equation A.1) and (Equation A.2) that $\theta^*_{1s}(d_3)$ is obtained by solving

$$\frac{1}{(1+\gamma)(1-\theta^*_{1s}(d_3))} = \frac{d_3}{(1+\gamma)\theta^*_{1s}(d_3)} - r_1. \tag{A.20}$$

We obtain two solutions

$$\theta_{1s,1}(d_3) = \frac{1}{2}\left[\frac{1+d_3+r_1(1+\gamma)}{r_1(1+\gamma)}\right] - \frac{1}{2}\left[\frac{\sqrt{\left(1+r_1(1+\gamma)\right)^2 + 2d_3(1-r_1(1+\gamma)) + d_3^2}}{r_1(1+\gamma)}\right], \tag{A.21}$$

$$\theta_{1s,2}(d_3) = \frac{1}{2}\left[\frac{1+d_3+r_1(1+\gamma)}{r_1(1+\gamma)}\right] + \frac{1}{2}\left[\frac{\sqrt{\left(1+r_1(1+\gamma)\right)^2 + 2d_3(1-r_1(1+\gamma)) + d_3^2}}{r_1(1+\gamma)}\right]. \tag{A.22}$$

Through a change of variables such that $\gamma_1 = 1 - \gamma \in [0, 1]$, the term $(1 + \gamma)$ can be replaced with $(2 - \gamma_1)$, and consequently it follows similarly to the proof of Proposition 1a that $\theta_{1s,2}(d_3) > 1$, while $\theta_{1s,1}(d_3) \in (0, 1)$. Therefore, a unique internal solution $\theta^*_{1s}(d_3)$ exists, and is equal to $\theta_{1s,1}(d_3)$. Finally, substituting $\theta^*_{1s}(d_3) = \theta_{1s,1}(d_3)$ in (Equation A.19), (Equation A.19) is equivalent to

$$r_2 - \frac{d_3}{(1+\gamma)\theta_{1s,1}(d_3)} + \frac{1}{(2-\gamma)} \geq 0. \tag{A.23}$$

This condition can be rewritten as

$$r_2 + \frac{1}{2-\gamma} - \frac{2d_3r_1}{1 + d_3 + r_1(1+\gamma) - \sqrt{(1 + d_3 + r_1(1+\gamma))^2 - 4(1+\gamma)d_3r_1}} \geq 0. \tag{A.24}$$

To express (Equation A.24) as a condition on r_1, we evaluate the derivative of the left-hand side of (Equation A.24) with respect to r_1, which is given by

$$\frac{-1 + d_3 - r_1(1+\gamma) - \sqrt{(1 - d_3 + r_1(1+\gamma))^2 + 4d_3}}{2\sqrt{(1 - d_3 + r_1(1+\gamma))^2 + 4d_3}}. \tag{A.25}$$

This expression is strictly negative because the term inside the square root is strictly greater than $(1 - d_3 + r_1(1+\gamma))^2 > 0$ and $-1 + d_3 - r_1(1+\gamma) < 0$ by $d_3 \in (0, 1]$, $\gamma \in [0, 1]$, and $r_1 > 0$. Thus, the left-hand side of (Equation A.24) is strictly decreasing in r_1 for $r_1 > 0$, and (Equation A.24) is satisfied by

$$r_1 \leq \underline{r}_s \tag{A.26}$$

if a solution $\underline{r}_s$ that satisfies (Equation A.24) at equality exists, and (Equation A.24) is not satisfied by any r_1 otherwise. In order to characterize the condition when a solution exists, we evaluate the left-hand side of (Equation A.24) as $r_1 \to +\infty$. This evaluates to $r_2 + 1/(2-\gamma) - 2d_3/[1 + \gamma - \sqrt{(1+\gamma)^2}]$, which approaches $-\infty$ as $r_1 \to +\infty$. This, together with the fact that the left-hand side of (Equation A.24) is strictly decreasing in $r_1 > 0$ implies that a solution $\underline{r}_s > r_2$ exists if and only if the left-hand side of (Equation A.24) evaluated at $r_1 = r_2$ is strictly greater than 0. This condition is equivalent to

$$r_2 + \frac{1}{2-\gamma} - \frac{2r_2 d_3}{1 + r_2(1+\gamma) + d_3 - \sqrt{(1 + r_2(1+\gamma) - d_3)^2 + 4d_3}} > 0. \tag{A.27}$$

Therefore, in the parameter region where (Equation A.27) holds, an equilibrium with $\theta^*_{1s}(d_3) \in (0, 1)$ and $\theta^*_{2s}(d_3) = 0$ exists if and only if $r_1 \leq \underline{r}_s$, where $\underline{r}_s$ solves (Equation A.24) at equality and satisfies $\underline{r}_s > r_2$. Conversely, in the parameter region where (Equation A.27) does not hold, we define $\underline{r}_s$ to be equal to r_2, which implies that $\theta^*_{1s}(d_3) \in (0, 1)$ and $\theta^*_{2s}(d_3) = 0$ cannot occur in equilibrium, as $r_1 > \underline{r}_s$ for all values of r_1 by definition.

Finally, we show that (Equation A.27) holds if and only if γ is sufficiently high. The derivative of the left-hand side of (Equation A.27) with respect to γ is given by

$$\frac{1}{(2-\gamma)^2} + \frac{2r_2^2 d_3 \left[1 - \frac{1 - d_3 + r_2(1+\gamma)}{\sqrt{(1 + r_2(1+\gamma) - d_3)^2 + 4d_3}}\right]}{(1 + d_3 + r_2(1+\gamma) - \sqrt{(1 + r_2(1+\gamma) + d_3)^2 - 4d_3 r_2(1+\gamma)})^2}.$$

In this expression, the first term is strictly positive because its denominator involves a squared term. The expression inside the square brackets in the numerator of the second term is in the range $(0, 1)$ due to $0 < 1 - d_3 + r_2(1+\gamma) < \sqrt{(1 + r_2(1+\gamma) - d_3)^2 + 4d_3}$ by $r_2 \in (0, 1)$, $\gamma \in [0, 1]$, and $d_3 \in (0, 1]$. In the denominator of the second term, the expression inside the square root can be rewritten as $(1 + r_2(1+\gamma) - d_3)^2 + 4d_3$, and it follows by $d_3 \in (0, 1]$ that this is strictly positive. Then, $1 + r_2(1+\gamma) + d_3 > \sqrt{(1 + r_2(1+\gamma) + d_3)^2 - 4d_3 r_2(1+\gamma)} > 0$ due to $r_2 \in (0, 1)$, $\gamma \in [0, 1]$, and $d_3 \in (0, 1]$, which implies that the denominator of the second term is strictly positive. Finally, $r_2 \in (0, 1)$ and $d_3 \in (0, 1]$ lead to the term outside the square brackets in the numerator of the second term to be strictly positive. Therefore, the left-hand side of (Equation A.27) is strictly increasing in γ for $\gamma \in [0, 1]$ and (Equation A.27) holds if and only if $\gamma > \tilde{\gamma}$, where $\tilde{\gamma}$ solves

$$r_2 + \frac{1}{2-\gamma} - \frac{2r_2 d_3}{1 + r_2(1+\gamma) + d_3 - \sqrt{(1 + r_2(1+\gamma) - d_3)^2 + 4d_3}} = 0. \tag{A.28}$$

We obtain two solutions

$$\tilde{\gamma}_1 = \frac{d_3 + 5r_2 + 2 - \sqrt{(d_3 - 3r_2 + 2)^2 + 24r_2}}{4r_2}, \tag{A.29}$$

$$\tilde{\gamma}_2 = \frac{d_3 + 5r_2 + 2 + \sqrt{(d_3 - 3r_2 + 2)^2 + 24r_2}}{4r_2}. \tag{A.30}$$

Consider the expression for $\tilde{\gamma}_2$ in (Equation A.30). The term inside the square root is strictly greater than $(d_3 - 3r_2 + 2)^2 \geq 0$ and is strictly positive by $r_2 \in (0, 1)$. This helps us to identify a lower bound on $\tilde{\gamma}_2$. If $d_3 - 3r_2 + 2 > 0$, we have $\tilde{\gamma}_2 > [d_3 + r_2 + 2]/2r_2$, which can be rewritten as $\tilde{\gamma}_2 > (1/r_2) + 0.5 + (d_3/2r_2)$. Moreover, $\tilde{\gamma}_2 > (1/r_2) + 0.5 + (d_3/2r_2) > 1$ by $d_3 \in (0, 1]$ and $r_2 \in (0, 1)$. If $d_3 - 3r_2 + 2 \leq 0$, we have $\tilde{\gamma}_2 > 8r_2/4r_2 > 1$. Therefore, $\tilde{\gamma}_2 > 1$ and can be omitted.

Consider the expression for $\tilde{\gamma}_1$ in (Equation A.29). The term inside the square root is strictly positive as shown above, and can be rewritten as $(d_3 + 3r_2 + 2)^2 - 12d_3r_2$. We have $\tilde{\gamma}_1 > 0$ because its numerator and denominator are strictly positive. The numerator is strictly positive because $d_3 + 5r_2 + 2 > 0$ and $(d_3 + 5r_2 + 2)^2 > (d_3 + 3r_2 + 2)^2 > (d_3 + 3r_2 + 2)^2 - 12d_3r_2$ by $d_3 \in (0, 1]$ and $r_2 \in (0, 1)$. The denominator is strictly positive by $r_2 \in (0, 1)$. Moreover, $\tilde{\gamma}_1 < 1$. Note that $\tilde{\gamma}_1 < 1$ is equivalent to $(d_3 + 5r_2 + 2 - 4r_2)^2 < (d_3 + 3r_2 + 2)^2 - 12d_3r_2$. Using simple algebra, this is equivalent to $-8r_2(1 - d_3 + r_2) < 0$, which is always true due to $r_2 \in (0, 1)$ and $d_3 \in (0, 1]$. Therefore, $\tilde{\gamma}_1 \in (0, 1)$ and we have a unique $\tilde{\gamma} = \tilde{\gamma}_1 \in (0, 1)$ that solves (Equation A.28).

To summarize, if $\gamma > \tilde{\gamma}$, then $\underline{r}_s > r_2$ is obtained by solving

$$r_2 + \frac{1}{2 - \gamma} - \frac{2d_3\underline{r}_s}{1 + d_3 + \underline{r}_s(1 + \gamma) - \sqrt{(1 + d_3 + \underline{r}_s(1 + \gamma))^2 - 4(1 + \gamma)d_3\underline{r}_s}} = 0, \tag{A.31}$$

and if $\gamma \leq \tilde{\gamma}$, $\underline{r}_s = r_2$ as defined above.

(c) Note that (Equation 2.3) and (Equation 2.4) are obtained by equating Zone 1 and Zone 2 drivers' expected utilities from staying and moving, respectively. Our approach here involves obtaining the solution θ_{1s} as a function of θ_{2s} for (Equation 2.3) and (Equation 2.4) separately, and we then show that the two functions intersect exactly once at interior values of $\theta_{1s}(d_3)$ and $\theta_{2s}(d_3)$ under conditions given in Proposition 1c. For brevity, we will drop d_3 from $\theta_{1s}(d_3)$ and $\theta_{2s}(d_3)$ and related expressions.

First, we use (Equation 2.3) to obtain the function $\theta_{1s}(\theta_{2s})$. We obtain two solutions

$$\overline{\theta}_{1s,1}(\theta_{2s}) = \frac{1+d_3+r_1(1+\gamma-(2-\gamma)\theta_{2s})+\sqrt{(1+d_3-r_1(1+\gamma+(2-\gamma)\theta_{2s}))^2+4r_1(1+\gamma+(2-\gamma)\theta_{2s})}}{2r_1(1+\gamma)}, \quad \text{(A.32)}$$

$$\underline{\theta}_{1s,1}(\theta_{2s}) = \frac{1+d_3+r_1(1+\gamma-(2-\gamma)\theta_{2s})-\sqrt{(1+d_3-r_1(1+\gamma+(2-\gamma)\theta_{2s}))^2+4r_1(1+\gamma+(2-\gamma)\theta_{2s})}}{2r_1(1+\gamma)}. \quad \text{(A.33)}$$

Consider the expression for $\overline{\theta}_{1s,1}(\theta_{2s})$ in (Equation A.32). The term inside the square root is strictly greater than $(1+d_3-r_1(1+\gamma+(2-\gamma)\theta_{2s}))^2 \geq 0$ and is strictly positive for all $\theta_{2s} \in (0,1)$ by $r_1 \in (0,1)$ and $\gamma \in [0,1]$, which allows us to identify a lower bound on $\overline{\theta}_{1s,1}(\theta_{2s})$. If $1+d_3-r_1(1+\gamma+(2-\gamma)\theta_{2s}) > 0$, then $\overline{\theta}_{1s,1}(\theta_{2s}) > [1+d_3-r_1(\theta_{2s}(2-\gamma))]/[r_1(1+\gamma)] > 1$. If $1+d_3-r_1(1+\gamma+(2-\gamma)\theta_{2s}) \leq 0$, then it follows that $\overline{\theta}_{1s,1}(\theta_{2s}) > 1$. We can hence rule out $\overline{\theta}_{1s,1}(\theta_{2s})$ as a possible solution and focus on $\underline{\theta}_{1s,1}(\theta_{2s})$.

Next, we use (Equation 2.4) to obtain θ_{1s} as a function of θ_{2s}, which yields

$$\theta_{1s,2}(\theta_{2s}) = \frac{-(2-\gamma)(-d_3+\theta_{2s}(1+d_3+r_2(2-\gamma)(1+\theta_{2s})))}{(1+\gamma)(1+r_2(2-\gamma)(1-\theta_{2s}))}.$$

In order to characterize the point at which $\underline{\theta}_{1s,1}(\theta_{2s})$ and $\theta_{1s,2}(\theta_{2s})$ intersect, we first evaluate their derivatives, $d\underline{\theta}_{1s,1}(\theta_{2s})/d\theta_{2s}$ and $d\theta_{1s,2}(\theta_{2s})/d\theta_{2s}$, given by

$$\frac{d\underline{\theta}_{1s,1}(\theta_{2s})}{d\theta_{2s}} = -\frac{(2-\gamma)}{2(1+\gamma)}\left[1+\frac{1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2s})}{\sqrt{(1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2s}))^2+4d_3}}\right], \quad \text{(A.34)}$$

$$\frac{d\theta_{1s,2}(\theta_{2s})}{d\theta_{2s}} = -\frac{1}{1+\gamma}\left[(2-\gamma)+\frac{d_3(2-\gamma)}{(1+r_2(2-\gamma)-r_2(2-\gamma)\theta_{2s})^2}\right], \quad \text{(A.35)}$$

and show that they are both strictly negative.

Consider the expression for $d\underline{\theta}_{1s,1}(\theta_{2s})/d\theta_{2s}$ from (Equation A.34). We first evaluate the expression inside the square brackets. The expression is strictly positive because the expression inside the square root in the denominator of the second term is strictly greater than $(1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2s}))^2 > 0$ and the numerator of the second term is strictly positive for all $\theta_{2s} \in (0,1)$ by $d_3 \in (0,1]$, $r_1 \in (0,1)$, and $\gamma \in [0,1]$. The term outside the square brackets is strictly negative by $\gamma \in [0,1]$. Therefore, $d\underline{\theta}_{1s,1}(\theta_{2s})/d\theta_{2s} < 0$.

Consider the expression for $d\theta_{1s,2}(\theta_{2s})/d\theta_{2s}$ from (Equation A.35). The term inside the square brackets is strictly positive for all $\theta_{2s} \in (0,1)$ by $\gamma \in [0,1]$ and $d_3 \in (0,1]$. The term outside the square brackets is strictly negative by $\gamma \in [0,1]$. Therefore, $d\theta_{1s,2}(\theta_{2s})/d\theta_{2s} < 0$.

Finally, we show that

$$\left|\frac{d\theta_{1s,2}(\theta_{2s})}{d\theta_{2s}}\right| - \left|\frac{d\underline{\theta}_{1s,1}(\theta_{2s})}{d\theta_{2s}}\right| = \frac{(2-\gamma)}{2(1+\gamma)}\left[1 - \frac{1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2s})}{\sqrt{(1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2s}))^2+4d_3}}\right] + \frac{2-\gamma}{1+\gamma}\left[\frac{d_3}{(1+r_2(2-\gamma)-r_2\theta_{2s}(2-\gamma))^2}\right] > 0.$$

The second term in the expression for $|d\theta_{1s,2}(\theta_{2s})/d\theta_{2s}| - |d\underline{\theta}_{1s,1}(\theta_{2s})/d\theta_{2s}|$ is strictly positive for all $\theta_{2s} \in (0,1)$ by $\gamma \in [0,1]$ and $d_3 \in (0,1]$. In the first term, the expression inside the square brackets is in the range $(0,1)$ because $(1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2s}))^2+4d_3 > 1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2s}) > 0$ for all $\theta_{2s} \in (0,1)$ by $d_3 \in (0,1]$, $\gamma \in [0,1]$, and $r_1 \in (0,1)$. Moreover, the expression outside the square brackets in the first term is strictly positive by $\gamma \in [0,1]$. Therefore, $|d\theta_{1s,2}(\theta_{2s})/d\theta_{2s}| - |d\underline{\theta}_{1s,1}(\theta_{2s})/d\theta_{2s}| > 0$, which implies that $\theta_{1s,2}$ declines faster with respect to θ_{2s} than $\underline{\theta}_{1s,1}$.

Since $d\underline{\theta}_{1s,1}(\theta_{2s})/d\theta_{2s} < 0$, $d\theta_{1s,2}(\theta_{2s})/d\theta_{2s} < 0$, and $|d\theta_{1s,2}(\theta_{2s})/d\theta_{2s}| - |d\underline{\theta}_{1s,1}(\theta_{2s})/d\theta_{2s}| > 0$, the functions $\underline{\theta}_{1s,1}(\theta_{2s})$ and $\theta_{1s,2}(\theta_{2s})$ will intersect exactly once in $\theta_{1s} \in (0,1)$ and $\theta_{2s} \in (0,1)$ if the following three conditions hold: $\underline{\theta}_{1s,1}(0) \in (0,1)$, $\underline{\theta}_{1s,1}(0) < \theta_{1s,2}(0)$, and $\hat{\theta}_{2s} < \tilde{\theta}_{2s}$, where $\hat{\theta}_{2s} \in (0,1)$ and $\tilde{\theta}_{2s}$ are such that $\theta_{1s,2}(\hat{\theta}_{2s}) = 0$ and $\underline{\theta}_{1s,1}(\tilde{\theta}_{2s}) = 0$.

First, we show that $\underline{\theta}_{1s,1}(0)$ is in the range $(0,1)$. Using simple algebra, $\underline{\theta}_{1s,1}(0)$ can be written as

$$\underline{\theta}_{1s,1}(0) = \frac{1}{2}\left[\frac{1+d_3+r_1(1+\gamma)}{r_1(1+\gamma)}\right] - \frac{1}{2}\left[\frac{\sqrt{\left(1+r_1(1+\gamma)\right)^2+2d_3(1-r_1(1+\gamma))+d_3^2}}{r_1(1+\gamma)}\right].$$

Note that $\underline{\theta}_{1s,1}(0)$ is equivalent to $\theta_{1s,1}(d_3)$ in (Equation A.21). Then it follows from the second paragraph after (Equation A.22) in the proof of Proposition 1b that $\underline{\theta}_{1s,1}(0) \in (0,1)$.

Next, we evaluate the condition $\underline{\theta}_{1s,1}(0) < \theta_{1s,2}(0)$. This condition is equivalent to $r_2 - d_3/[(1+\gamma)\theta_{1s,1}(d_3)] + 1/(2-\gamma) < 0$, where $\theta_{1s,1}(d_3)$ is given by (Equation A.21). Therefore, $\underline{\theta}_{1s,1}(0) < \theta_{1s,2}(0)$ is the opposite of (Equation A.26), as established in the proof of Proposition 1b, and is equivalent to $r_1 > \underline{r}_s$.

Finally, we examine the condition $\hat{\theta}_{2s} < \tilde{\theta}_{2s}$, where $\hat{\theta}_{2s}$ and $\tilde{\theta}_{2s}$ satisfy $\theta_{1s,2}(\hat{\theta}_{2s}) = 0$ and $\underline{\theta}_{1s,1}(\tilde{\theta}_{2s}) = 0$. Note that the solutions to the equation $\theta_{1s,2}(\hat{\theta}_{2s}) = 0$, $\hat{\theta}_{2s,1}$ and $\hat{\theta}_{2s,2}$, are equivalent to $\theta_{2s,1}(d_3)$ and $\theta_{2s,2}(d_3)$ characterized in (Equation A.15) and (Equation A.16), respectively, in the proof of Proposition 1a. Then it follows from the two paragraphs below (Equation A.16) in the proof of Proposition 1a that $\hat{\theta}_{2s,1} \in (0,1)$, while $\hat{\theta}_{2s,2} > 1$ can be omitted.

Furthermore, the solution to the equation $\underline{\theta}_{1s,1}(\tilde{\theta}_{2s}) = 0$ equals $\tilde{\theta}_{2s} = d_3(1+\gamma)/[(2-\gamma)(1+r_1(1+\gamma))]$, which is strictly positive by $d_3 \in (0,1]$, $r_1 \in (0,1)$, and $\gamma \in [0,1]$. Lastly, we can show by algebra that the condition $\hat{\theta}_{2s,1} < \tilde{\theta}_{2s}$ is equivalent to $r_1 - d_3/[(2-\gamma)\theta_{2s,1}(d_3)] + 1/(1+\gamma) < 0$, where $\theta_{2s,1}(d_3)$ is defined in (Equation A.15). This condition is the opposite of (Equation A.17), as established in the proof of Proposition 1a, and is equivalent to $r_1 < \overline{r}_s$.

(d) It follows from the proof of Proposition 1b that $\underline{r}_s > r_2$ if and only if $\gamma > \tilde{\gamma} = \tilde{\gamma}_1$, where $\tilde{\gamma}_1$ is given by (Equation A.29). By simple algebra, $\tilde{\gamma}_1 > 0.5$ can be shown to be equivalent to $(d_3+3r_2+2)^2 > (d_3-3r_2+2)^2 + 24r_2$, which holds by $d_3 \in (0,1]$ and $r_2 \in (0,1)$.

Proof of Proposition 2

(a) Zone 1 drivers do not move in equilibrium if and only if, given θ_{2f}^*, i.e., the equilibrium proportion of Zone 2 drivers that move, their expected earnings from staying are greater than or equal to those from moving for $\theta_{1f}^* = 0$. It follows from (Equation A.5) and (Equation A.6) that Zone 1 drivers do not move in equilibrium if and only if

$$r_1 \geq \frac{d_3}{(2-\gamma)\theta^*_{2f}} - \frac{2d_1}{1+\gamma}. \tag{A.36}$$

At the equilibrium proportion θ^*_{2f}, by definition, Zone 2 drivers are indifferent between staying and moving, given $\theta^*_{1f} = 0$. It follows from (Equation A.7) and (Equation A.8) that θ^*_{2f} is obtained by solving

$$\frac{2d_2}{(2-\gamma)(1-\theta^*_{2f})} = \frac{d_3}{(2-\gamma)\theta^*_{2f}} - r_2. \tag{A.37}$$

We obtain two solutions

$$\theta_{2f,1} = \frac{2d_2 + d_3 + r_2(2-\gamma) - \sqrt{(2d_2 + d_3 - r_2(2-\gamma))^2 + 8r_2d_2(2-\gamma)}}{2r_2(2-\gamma)}, \tag{A.38}$$

$$\theta_{2f,2} = \frac{2d_2 + d_3 + r_2(2-\gamma) + \sqrt{(2d_2 + d_3 - r_2(2-\gamma))^2 + 8r_2d_2(2-\gamma)}}{2r_2(2-\gamma)}. \tag{A.39}$$

In expression (Equation A.39) for $\theta_{2f,2}$, the term inside the square root is strictly greater than $(2d_2 + d_3 - r_2(2-\gamma))^2 \geq 0$ and is strictly positive by $r_2 \in (0,1)$, $d_2 \in (0,1]$, and $\gamma \in [0,1]$, which allows us to identify a lower bound on $\theta_{2f,2}$. If $2d_2 + d_3 - r_2(2-\gamma) > 0$, we have $\theta_{2f,2} > [2d_2 + d_3]/[r_2(2-\gamma)] > 1$. If $2d_2 + d_3 - r_2(2-\gamma) \leq 0$, we have $\theta_{2f,2} > 1$. Hence, $\theta_{2f,2}$ can be ruled out as a possible solution.

Consider the expression for $\theta_{2f,1}$ in (Equation A.38). $\theta_{2f,1} > 0$ because its numerator and denominator are both strictly positive. To see this point, note that the numerator can be rewritten as $[2d_2 + d_3 + r_2(2-\gamma)] - [\sqrt{(2d_2 + d_3 + r_2(2-\gamma))^2 - 4r_2d_3(2-\gamma)}]$, in which the two terms inside the square brackets are strictly positive, and the square of the first term is strictly greater than that of the second term by $r_2 \in (0,1)$, $d_3 \in (0,1]$, and $\gamma \in [0,1]$. The denominator is strictly positive by $r_2 \in (0,1)$ and $\gamma \in [0,1]$. The term inside the square root in (Equation A.38) is strictly greater than $(2d_2 + d_3 - r_2(2-\gamma))^2 \geq 0$. This allows us to identify an upper bound on

$\theta_{2f,1}$. If $2d_2 + d_3 - r_2(2-\gamma) > 0$, we have $\theta_{2f,1} < 1$. If $2d_2 + d_3 - r_2(2-\gamma) \le 0$, we have $\theta_{2f,1} < [2d_2 + d_3]/[r_2(2-\gamma)] \le 1$. Consequently, a unique internal solution θ^*_{2f} exists, and is equal to $\theta_{2f,1}$. Substituting $\theta^*_{2f} = \theta_{2f,1}$ in (Equation A.36), (Equation A.36) is equivalent to

$$r_1 \ge \overline{r}_f = \frac{d_3}{(2-\gamma)\theta_{2f,1}} - \frac{2d_1}{1+\gamma}. \tag{A.40}$$

In our original notation, $\overline{r}_f$ is equivalent to

$$\overline{r}_f = \frac{2}{n^2}\left(\frac{d_3 n^2 p r_2}{(2d_2+d_3)\,p^2 + (2-\gamma)n^2 r_2 - np\sqrt{\left(\frac{(2d_2+d_3)p}{n} + \frac{(2-\gamma)nr_2}{p}\right)^2 - 4(2-\gamma)d_3 r_2}} - \frac{pd_1}{1+\gamma}\right). \tag{A.41}$$

(b) Zone 2 drivers do not move in equilibrium if and only if, given θ^*_{1f}, i.e., the equilibrium proportion of Zone 1 drivers that move, their expected earnings from staying are greater than or equal to those from moving for $\theta^*_{2f} = 0$. It follows from (Equation A.7) and (Equation A.8) that Zone 2 drivers do not move in equilibrium if and only if

$$r_2 \ge \frac{d_3}{(1+\gamma)\theta^*_{1f}} - \frac{2d_2}{2-\gamma}. \tag{A.42}$$

At the equilibrium proportion θ^*_{1f}, by definition, Zone 1 drivers are indifferent between staying and moving, given $\theta^*_{2f} = 0$. It follows from (Equation A.5) and (Equation A.6) that θ^*_{1f} is obtained by solving

$$\frac{2d_1}{(1+\gamma)(1-\theta^*_{1f})} = \frac{d_3}{(1+\gamma)\theta^*_{1f}} - r_1. \tag{A.43}$$

We obtain two solutions

$$\theta_{1f,1} = \frac{2d_1 + d_3 + r_1(1+\gamma) - \sqrt{(2d_1 + d_3 - r_1(1+\gamma))^2 + 8r_1 d_1(1+\gamma)}}{2r_1(1+\gamma)}, \tag{A.44}$$

$$\theta_{1f,2} = \frac{2d_1 + d_3 + r_1(1+\gamma) + \sqrt{(2d_1 + d_3 - r_1(1+\gamma))^2 + 8r_1 d_1(1+\gamma)}}{2r_1(1+\gamma)}. \tag{A.45}$$

Consider the expression for $\theta_{1f,2}$ in (Equation A.45). The term inside the square root is strictly greater than $(2d_1 + d_3 - r_1(1+\gamma))^2 \geq 0$ and is strictly positive by $r_1 \in (0,1)$, $d_1 \in (0,1]$, and $\gamma \in [0,1]$, which allows us to identify a lower bound on $\theta_{1f,2}$. If $2d_1 + d_3 - r_1(1+\gamma) > 0$, we have $\theta_{1f,2} > [2d_1 + d_3]/[r_1(1+\gamma)] > 1$. If $2d_1 + d_3 - r_1(1+\gamma) \leq 0$, we have $\theta_{1f,2} > 1$. Hence, $\theta_{1f,2}$ can be ruled out as a possible solution.

Consider the expression for $\theta_{1f,1}$ in (Equation A.44). $\theta_{1f,1} > 0$ because its numerator and denominator are both strictly positive. To see this point, note that the numerator can be rewritten as $[2d_1 + d_3 + r_1(1+\gamma)] - [\sqrt{(2d_1 + d_3 + r_1(1+\gamma))^2 - 4r_1 d_3(1+\gamma)}]$, in which the two terms inside the square brackets are strictly positive, and the square of the first term is strictly greater than that of the second term by $r_1 \in (0,1)$, $d_3 \in (0,1]$, and $\gamma \in [0,1]$. The denominator is strictly positive by $r_1 \in (0,1)$ and $\gamma \in [0,1]$. The term inside the square root in (Equation A.44) is strictly greater than $(2d_1 + d_3 - r_1(1+\gamma))^2 \geq 0$. This allows use to identify an upper bound on $\theta_{1f,1}$. If $2d_1 + d_3 - r_1(1+\gamma) > 0$, we have $\theta_{1f,1} < 1$. If $2d_1 + d_3 - r_1(1+\gamma) \leq 0$, we have $\theta_{1f,1} < [2d_1 + d_3]/[r_1(1+\gamma)] \leq 1$. Consequently, a unique internal solution θ^*_{1f} exists, and is equal to $\theta_{1f,1}$. Substituting $\theta^*_{1f} = \theta_{1f,1}$ in (Equation A.42), (Equation A.42) is equivalent to

$$r_2 - \frac{d_3}{(1+\gamma)\theta_{1f,1}} + \frac{2d_2}{2-\gamma} \geq 0. \tag{A.46}$$

This condition can be rewritten as

$$r_2 + \frac{2d_2}{2-\gamma} - \frac{2d_3 r_1}{2d_1 + d_3 + r_1(1+\gamma) - \sqrt{(2d_1 + d_3 + r_1(1+\gamma))^2 - 4(1+\gamma)d_3 r_1}} \geq 0. \tag{A.47}$$

To express (Equation A.47) as a condition on r_1, we analyze the derivative of its left-hand side with respect to r_1, which evaluates to

$$\frac{-2d_1 + d_3 - r_1(1+\gamma) - \sqrt{(2d_1 + d_3 - r_1(1+\gamma))^2 + 8r_1 d_1(1+\gamma)}}{2\sqrt{(2d_1 + d_3 - r_1(1+\gamma))^2 + 8r_1 d_1(1+\gamma)}}. \tag{A.48}$$

Note that in (Equation A.48), the term inside the square root is strictly greater than $(2d_1 + d_3 - r_1(1+\gamma))^2 \geq 0$, and is strictly positive by $r_1 > 0$, $d_1 \in (0,1]$, and $\gamma \in [0,1]$. Then, we can identify an upper bound on the numerator of the expression in (Equation A.48). If $2d_1 + d_3 - r_1(1+\gamma) > 0$, the numerator is strictly less than $-4d_1$, which is strictly negative by $d_1 \in (0,1]$. If $2d_1 + d_3 - r_1(1+\gamma) \leq 0$, the numerator is strictly less than $2(d_3 - r_1(1+\gamma))$, and it follows from $2d_1 + d_3 - r_1(1+\gamma) \leq 0$ and $d_1 \in (0,1]$ and that $d_3 - r_1(1+\gamma) \leq -2d_1 < 0$ that the numerator is strictly negative. Moreover, the denominator of (Equation A.48) is strictly positive because the term inside the square root is strictly positive as shown above, which leads to (Equation A.48) being strictly negative. Thus, the left-hand side of (Equation A.47) is strictly decreasing in r_1 for $r_1 > 0$, and (Equation A.47) is satisfied by

$$r_1 \leq \underline{r}_f, \tag{A.49}$$

if a solution $\underline{r}_f$ that satisfies (Equation A.47) at equality exists, and (Equation A.47) is not satisfied by any r_1 otherwise. In order to characterize the condition when a solution exists, we evaluate the left-hand side of (Equation A.47) as $r_1 \to +\infty$. This evaluates to $r_2 + 2d_2/(2-\gamma) - 2d_3/[1+\gamma - \sqrt{(1+\gamma)^2}]$, which approaches $-\infty$ as $r_1 \to +\infty$. This, together with the fact that the left-hand side of (Equation A.47) is strictly decreasing in $r_1 > 0$ implies that a solution $\underline{r}_f > r_2$ exists if and only if the left-hand side of (Equation A.47) evaluated at $r_1 = r_2$ is strictly greater than 0. This condition is equivalent to

$$r_2 + \frac{2d_2}{2-\gamma} - \frac{2d_3 r_2}{2d_1 + d_3 + r_2(1+\gamma) - \sqrt{(2d_1 + d_3 + r_2(1+\gamma))^2 - 4(1+\gamma)d_3 r_2}} > 0. \tag{A.50}$$

Therefore, in the parameter region where (Equation A.50) holds, an equilibrium with $\theta^*_{1f} \in (0,1)$ and $\theta^*_{2f} = 0$ exists if and only if $r_1 \leq \underline{r}_f$, where $\underline{r}_f$ solves

$$r_2 + \frac{2d_2}{2-\gamma} - \frac{2d_3 \underline{r}_f}{2d_1 + d_3 + \underline{r}_f(1+\gamma) - \sqrt{\left(2d_1 + d_3 + \underline{r}_f(1+\gamma)\right)^2 - 4(1+\gamma)d_3 \underline{r}_f}} = 0, \tag{A.51}$$

and satisfies $\underline{r}_f > r_2$. Conversely, in the parameter region where (Equation A.50) does not hold, we define $\underline{r}_f$ to be equal to r_2, which implies that $\theta^*_{1f} \in (0,1)$ and $\theta^*_{2f} = 0$ cannot occur in equilibrium, as $r_1 > \underline{r}_f$ for all r_1 by definition.

(c) Note that (Equation 2.7) and (Equation 2.8) are obtained by equating Zone 1 and Zone 2 drivers' expected utilities from staying and moving, respectively. Our approach here involves obtaining the solution θ_{1f} as a function of θ_{2f} for (Equation 2.7) and (Equation 2.8) separately, and we then show that the two functions intersect exactly once at interior values of θ_{1f} and θ_{2f} under the conditions given in Proposition 2c.

First, we use (Equation 2.7) to obtain the function $\theta_{1f}(\theta_{2f})$. We obtain two solutions

$$\overline{\theta}_{1f,1}(\theta_{2f}) = \frac{2d_1 + d_3 + r_1(1+\gamma-\theta_{2f}(2-\gamma)) + \sqrt{(2d_1+d_3-r_1(1+\gamma+\theta_{2f}(2-\gamma)))^2 + 8r_1d_1(1+\gamma+\theta_{2f}(2-\gamma))}}{2r_1(1+\gamma)}, \tag{A.52}$$

$$\underline{\theta}_{1f,1}(\theta_{2f}) = \frac{2d_1 + d_3 + r_1(1+\gamma-\theta_{2f}(2-\gamma)) - \sqrt{(2d_1+d_3-r_1(1+\gamma+\theta_{2f}(2-\gamma)))^2 + 8r_1d_1(1+\gamma+\theta_{2f}(2-\gamma))}}{2r_1(1+\gamma)}. \tag{A.53}$$

Consider the expression for $\overline{\theta}_{1f,1}(\theta_{2f})$ in (Equation A.52). The term inside the square root is strictly greater than $(2d_1 + d_3 - r_1(1+\gamma+\theta_{2f}(2-\gamma)))^2 \geq 0$ and is strictly positive for all $\theta_{2f} \in (0,1)$ by $r_1 \in (0,1)$, $d_1 \in (0,1]$, and $\gamma \in [0,1]$. This observation allows us to identify a lower bound on $\overline{\theta}_{1f,1}(\theta_{2f})$. If $2d_1 + d_3 - r_1(1+\gamma+(2-\gamma)\theta_{2f}) > 0$, we have $\overline{\theta}_{1f,1}(\theta_{2f}) > [2d_1 + d_3 - r_1\theta_{2f}(2-\gamma)]/[r_1(1+\gamma)] > 1$. If $2d_1 + d_3 - r_1(1+\gamma+(2-\gamma)\theta_{2f}) \leq 0$, we have $\overline{\theta}_{1f,1}(\theta_{2f}) > 1$. We can hence rule out $\overline{\theta}_{1f,1}(\theta_{2f})$ as a possible solution and focus on $\underline{\theta}_{1f,1}(\theta_{2f})$.

Next, we use (Equation 2.8) to obtain θ_{1f} as a function of θ_{2f}. This gives

$$\theta_{1f,2}(\theta_{2f}) = \frac{(2-\gamma)(d_3 - \theta_{2f}(2d_2 + d_3 + r_2(2-\gamma) - r_2\theta_{2f}(2-\gamma)))}{(1+\gamma)(2r_2 + 2d_2 - r_2\gamma - r_2\theta_{2f}(2-\gamma))}.$$

In order to characterize the point at which $\underline{\theta}_{1f,1}(\theta_{2f})$ and $\theta_{1f,2}(\theta_{2f})$ intersect, we first evaluate their derivatives, $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}$ and $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}$, given by

$$\frac{d\underline{\theta}_{1f,1}(\theta_{2f})}{d\theta_{2f}} = -\frac{(2-\gamma)}{2(1+\gamma)}\left[1+\frac{2d_1-d_3+r_1((1+\gamma)+(2-\gamma)\theta_{2f})}{\sqrt{(2d_1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2f}))^2+8d_1d_3}}\right], \tag{A.54}$$

$$\frac{d\theta_{1f,2}(\theta_{2f})}{d\theta_{2f}} = -\frac{1}{1+\gamma}\left[(2-\gamma)+\frac{2d_2d_3(2-\gamma)}{((1-\theta_{2f})r_2(2-\gamma)+2d_2)^2}\right], \tag{A.55}$$

and show that they are both strictly negative.

Consider the expression for $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}$, which is characterized in (Equation A.54). We first evaluate the expression inside the square brackets. Here, the expression inside the square root in the denominator of the second term is strictly greater than $(2d_1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2f}))^2 \geq 0$ and is strictly positive for all $\theta_{2f} \in (0,1)$ by $r_1 \in (0,1)$, $\gamma \in [0,1]$, $d_1 \in (0,1]$, and $d_3 \in (0,1]$. This allows us to identify an upper bound on $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}$. $0 < |2d_1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2f})| < \sqrt{(2d_1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2f}))^2+8d_1d_3}$ by $\{d_1,d_3\} \in (0,1]$, which leads the expression inside the square brackets to be in the range $(0,1)$ if $2d_1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2f}) < 0$, and strictly positive otherwise. Then it follows that $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f} < 0$ by $\gamma \in [0,1]$.

Consider the expression for $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}$ from (Equation A.55). The term inside the square brackets is strictly positive for all $\theta_{2f} \in (0,1)$, while the term outside the square brackets is strictly negative by $\gamma \in [0,1]$ and $\{d_2,d_3\} \in (0,1]$. Therefore, $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f} < 0$.

Finally, we show that

$$\begin{aligned}\left|\frac{d\theta_{1f,2}(\theta_{2f})}{d\theta_{2f}}\right| - \left|\frac{d\underline{\theta}_{1f,1}(\theta_{2f})}{d\theta_{2f}}\right| = \\ \frac{(2-\gamma)}{2(1+\gamma)}\left[1-\frac{2d_1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2f})}{\sqrt{(2d_1-d_3+r_1(1+\gamma+(2-\gamma)\theta_{2f}))^2+8d_1d_3}}\right]+ \\ \frac{2-\gamma}{1+\gamma}\left[\frac{2d_2d_3}{(2r_2+2d_2-r_2\gamma-r_2\theta_{2f}(2-\gamma))^2}\right] > 0.\end{aligned}$$

The second term in the expression for $|d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}| - |d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}|$ is strictly positive for all $\theta_{2f} \in (0,1)$ by $\gamma \in [0,1]$ and $\{d_2,d_3\} \in (0,1]$. It follows similarly to the analysis of $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}$ above that the first term is strictly positive for all $\theta_{2f} \in (0,1)$, and hence

$|d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}| - |d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}| > 0$. This implies that $\theta_{1f,2}$ declines faster in θ_{2f} than $\underline{\theta}_{1f,1}$.

Since $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f} < 0$, $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f} < 0$, and $|d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}| - |d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}| > 0$, the functions $\underline{\theta}_{1f,1}(\theta_{2f})$ and $\theta_{1f,2}(\theta_{2f})$ will intersect exactly once in $\theta_{1f} \in (0,1)$ and $\theta_{2f} \in (0,1)$ if the following three conditions hold: $\underline{\theta}_{1f,1}(0) \in (0,1)$, $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0)$, and $\hat{\theta}_{2f} < \tilde{\theta}_{2f}$, where $\hat{\theta}_{2f} \in (0,1)$ and $\tilde{\theta}_{2f}$ are such that $\theta_{1f,2}(\hat{\theta}_{2f}) = 0$ and $\underline{\theta}_{1f,1}(\tilde{\theta}_{2f}) = 0$.

First, we show that $\underline{\theta}_{1f,1}(0)$ is in the range $(0,1)$. By simple algebra, $\underline{\theta}_{1f,1}(0)$ can be written as

$$\underline{\theta}_{1f,1}(0) = \frac{2d_1 + d_3 + r_1(1+\gamma) - \sqrt{(2d_1 + d_3 - r_1(1+\gamma))^2 + 8r_1 d_1(1+\gamma)}}{2r_1(1+\gamma)}. \tag{A.56}$$

Note that the expression for $\underline{\theta}_{1f,1}(0)$ in (Equation A.56) is equivalent to that for $\theta_{1f,1}$ in (Equation A.44). Then it follows from the second paragraph after (Equation A.45) in the proof of Proposition 2b that $\underline{\theta}_{1f,1}(0) \in (0,1)$.

Next, we examine the condition $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0)$. By algebra, we can show that this condition is equivalent to $r_2 - d_3/[(1+\gamma)\theta_{1f,1}] + 2d_2/(2-\gamma) < 0$, where $\theta_{1f,1}$ is given by (Equation A.44). Therefore, $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0)$ is the opposite of (Equation A.49), as established in the proof of Proposition 2b, and is equivalent to $r_1 > \underline{r}_f$.

Finally, we examine the condition $\hat{\theta}_{2f} < \tilde{\theta}_{2f}$, where $\hat{\theta}_{2f}$ and $\tilde{\theta}_{2f}$ satisfy $\theta_{1f,2}(\hat{\theta}_{2f}) = 0$ and $\underline{\theta}_{1f,1}(\tilde{\theta}_{2f}) = 0$. Note that the solutions to the equation $\theta_{1f,2}(\hat{\theta}_{2f}) = 0$, $\hat{\theta}_{2f,1}$ and $\hat{\theta}_{2f,2}$ are equivalent to $\theta_{2f,1}$ and $\theta_{2f,2}$ characterized in (Equation A.38) and (Equation A.39), respectively, in the proof of Proposition 2a. Then, it follows from the two paragraphs below (Equation A.39) in the proof of Proposition 2a that $\hat{\theta}_{2f,1} \in (0,1)$, while $\hat{\theta}_{2f,2} > 1$ can be omitted.

Furthermore, the solution to $\underline{\theta}_{1f,1}(\tilde{\theta}_{2f}) = 0$ equals $\tilde{\theta}_{2f} = d_3(1+\gamma)/[(2-\gamma)(2d_1 + r_1(1+\gamma))]$. It follows from $\{d_1, d_3\} \in (0,1]$ and $\gamma \in [0,1]$ that $\tilde{\theta}_{2f} > 0$. Lastly, we can show by algebra that the condition $\hat{\theta}_{2f,1} < \tilde{\theta}_{2f}$ is equivalent to $r_1 - d_3/[(2-\gamma)\theta_{2f,1}] + 2d_1/(1+\gamma) < 0$, where $\theta_{2f,1}$ is defined in (Equation A.38). This condition is the opposite of (Equation A.40), as established in the proof of Proposition 2a, and is equivalent to $r_1 < \overline{r}_f$.

Proof of Proposition 3

(a) Zone 1 drivers do not move in equilibrium if and only if, given $\theta^*_{2\ell}(d_3)$, i.e., the equilibrium proportion of Zone 2 drivers that move, their expected earnings from staying are greater than or equal to those from moving for $\theta^*_{1\ell} = 0$. It follows from (Equation A.11) and (Equation A.12) that Zone 1 drivers do not move in equilibrium if and only if

$$r_1 \geq E\left[\frac{d_3}{(2-\gamma)\theta^*_{2\ell}(d_3)}\right] - \frac{1}{1+\gamma}. \tag{A.57}$$

At the equilibrium proportion $\theta^*_{2\ell}(d_3)$, by definition, Zone 2 drivers are indifferent between staying and moving in equilibrium, given $\theta^*_{1\ell} = 0$. It follows from (Equation A.9) and (Equation A.10) that $\theta^*_{2\ell}(d_3)$ is obtained by solving

$$\frac{1}{(2-\gamma)(1-\theta^*_{2\ell}(d_3))} = \frac{d_3}{(2-\gamma)\theta^*_{2\ell}(d_3)} - r_2. \tag{A.58}$$

We obtain two solutions

$$\theta_{2\ell,1}(d_3) = \frac{1}{2}\left[\frac{1+d_3+r_2(2-\gamma)}{r_2(2-\gamma)}\right] - \frac{1}{2}\left[\frac{\sqrt{\left(1+r_2(2-\gamma)\right)^2 + 2d_3(1-r_2(2-\gamma)) + d_3^2}}{r_2(2-\gamma)}\right], \tag{A.59}$$

$$\theta_{2\ell,2}(d_3) = \frac{1}{2}\left[\frac{1+d_3+r_2(2-\gamma)}{r_2(2-\gamma)}\right] + \frac{1}{2}\left[\frac{\sqrt{\left(1+r_2(2-\gamma)\right)^2 + 2d_3(1-r_2(2-\gamma)) + d_3^2}}{r_2(2-\gamma)}\right]. \tag{A.60}$$

Note that $\theta_{2\ell,1}(d_3) = \theta_{2s,1}(d_3)$ and $\theta_{2\ell,2}(d_3) = \theta_{2s,2}(d_3)$ where $\theta_{2s,1}(d_3)$ and $\theta_{2s,2}(d_3)$ are characterized in (Equation A.15) and (Equation A.16), respectively. It follows from the proof of Proposition 1a that $\theta_{2s,2}(d_3) > 1$ and $\theta_{2s,1}(d_3) \in (0,1)$ for all $d_3 \in (0,1]$. Furthermore, it is straightforward to show that when $\theta^*_{1\ell} = 0$ and $d_3 = 0$, Zone 2 drivers do not move as (Equation A.9) evaluated at any $\theta^*_{2\ell}(d_3) > 0$ dominates (Equation A.10). Consequently, a unique solution $\theta^*_{2\ell}(d_3)$ exists, and is equal to $\theta_{2\ell,1}(d_3)$ for all $d_3 \in (0,1]$ and equals 0 for $d_3 = 0$. Substituting $\theta^*_{2\ell}(d_3)$ in (Equation A.57), (Equation A.57) is equivalent to $r_1 \geq \overline{r}_\ell$, where $\overline{r}_\ell$ in our original notation is given by

$$\overline{r}_\ell = E\Bigg[\frac{2pd_3r_2}{n\left(p+(2-\gamma)r_2-p\left(\sqrt{\frac{d_3^2}{n^2}+\frac{2d_3(p-(2-\gamma)r_2)}{np}+\frac{(p+(2-\gamma)r_2)^2}{p^2}}\right)\right)+d_3p}\Bigg]-\frac{p}{1+\gamma}. \tag{A.61}$$

(b) Zone 2 drivers always choose to stay in their zone in equilibrium if and only if, given $\theta^*_{1\ell}$, i.e., the equilibrium proportion of Zone 1 drivers that move, their expected earnings from staying are greater than or equal to those from moving for $\theta^*_{2\ell}(d_3) = 0$ for all $d_3 \in [0,1]$. It follows from (Equation A.9) and (Equation A.10), that given d_3, Zone 2 drivers choose to stay in equilibrium if and only if

$$r_2 \geq \frac{d_3}{(1+\gamma)\theta^*_{1\ell}} - \frac{1}{2-\gamma}. \tag{A.62}$$

Since the expression on the right-hand side of (Equation A.62) is strictly increasing in d_3, it follows that (Equation A.62) holds for all $d_3 \in [0,1]$ if and only if it holds at $d_3 = 1$. That is, Zone 2 drivers choose to stay for all $d_3 \in [0,1]$ in equilibrium if and only if

$$r_2 \geq \frac{1}{(1+\gamma)\theta^*_{1\ell}} - \frac{1}{2-\gamma}. \tag{A.63}$$

At the equilibrium proportion $\theta^*_{1\ell}$, by definition, Zone 1 drivers are indifferent between staying and moving for all $d_3 \in [0,1]$ given $\theta^*_{2\ell}(d_3) = 0$. It follows from (Equation A.11) and (Equation A.12) that $\theta^*_{1\ell}$ is obtained by solving

$$\frac{1}{(1+\gamma)(1-\theta^*_{1\ell})} = E\left[\frac{d_3}{(1+\gamma)\theta^*_{1\ell}}\right] - r_1 = \frac{1}{2(1+\gamma)\theta^*_{1\ell}} - r_1. \tag{A.64}$$

Solving (Equation A.64) for $\theta^*_{1\ell}$ gives two solutions

$$\theta_{1\ell,1} = \frac{2}{3+2r_1(1+\gamma)+\sqrt{9+4r_1^2(1+\gamma)^2+4r_1(1+\gamma)}}, \tag{A.65}$$

$$\theta_{1\ell,2} = \frac{2}{3+2r_1(1+\gamma)-\sqrt{9+4r_1^2(1+\gamma)^2+4r_1(1+\gamma)}}. \tag{A.66}$$

Consider the expression for $\theta_{1\ell,2}$ in (Equation A.66). The term inside the square root can be rewritten as $(1+2r_1(1+\gamma))^2+8$, which is strictly greater than $(1+2r_1(1+\gamma))^2 > 0$ and is strictly positive by $r_1 \in (0,1)$ and $\gamma \in [0,1]$. This implies that in the denominator, we have $3+2r_1(1+\gamma)-\sqrt{(1+2r_1(1+\gamma))^2+8} < 3+2r_1(1+\gamma)-1-2r_1(1+\gamma) = 2$. Thus, $\theta_{1\ell,2} > 1$.

Consider the expression for $\theta_{1\ell,1}$ in (Equation A.65). Since the term inside the square root is strictly positive and $3+2r_1(1+\gamma) > 0$ by $r_1 \in (0,1)$ and $\gamma \in [0,1]$, the denominator is strictly greater than 3, and therefore, $\theta_{1\ell,1} \in (0,1)$. Consequently, a unique interior solution $\theta^*_{1\ell}$ exists, and is equal to $\theta_{1\ell,1}$. Substituting $\theta^*_{1\ell} = \theta_{1\ell,1}$ in (Equation A.63) and rearranging terms, (Equation A.63) is equivalent to

$$r_2 + \frac{1}{2-\gamma} - \frac{4r_1}{2r_1(1+\gamma)+3-\sqrt{4(1+\gamma)r_1\left(r_1(1+\gamma)+1\right)+9}} \geq 0. \tag{A.67}$$

To express (Equation A.67) in terms of r_1, we analyze the derivative of the left-hand side of the equation with respect to r_1, which is given by

$$\frac{-1-2r_1(1+\gamma)-\sqrt{9+4r_1^2(1+\gamma)^2+4r_1(1+\gamma)}}{\sqrt{9+4r_1^2(1+\gamma)^2+4r_1(1+\gamma)}}.$$

The term inside the square root in this expression is strictly positive as shown in the paragraph below (Equation A.66), and hence the denominator is strictly positive. Moreover, $-1-2r_1(1+\gamma) < 0$ follows from $r_1 > 0$ and $\gamma \in [0,1]$, which implies that the numerator is strictly negative. Thus, the left-hand side of (Equation A.67) is strictly decreasing in r_1 for $r_1 > 0$, and (Equation A.67) is satisfied by

$$r_1 \leq \underline{r}_\ell \tag{A.68}$$

if a solution $\underline{r}_\ell$ that satisfies (Equation A.67) at equality exists, and (Equation A.67) is not satisfied by any r_1 otherwise. In order to characterize the condition when a solution exists, we evaluate the left-hand side of (Equation A.67) as $r_1 \to +\infty$. This evaluates to $r_2 + 1/(2-\gamma) - 2/[1+\gamma - \sqrt{(1+\gamma)^2}]$, which approaches $-\infty$ as $r_1 \to +\infty$. This, together with the fact that the left-hand side of (Equation A.67) is strictly decreasing in $r_1 > 0$ implies that a solution $\underline{r}_\ell > r_2$ exists if and only if the left-hand side of (Equation A.67) evaluated at $r_1 = r_2$ is strictly greater than 0. This condition is equivalent to

$$r_2 + \frac{1}{2-\gamma} - \frac{4r_2}{2r_2(1+\gamma)+3-\sqrt{4(1+\gamma)r_2\left(r_2(1+\gamma)+1\right)+9}} > 0. \tag{A.69}$$

Therefore, in the parameter region where (Equation A.69) holds, an equilibrium with $\theta^*_{1\ell} \in (0,1)$ and $\theta^*_{2\ell}(d_3) = 0$ for all $d_3 \in [0,1]$ exists if and only if $r_1 \leq \underline{r}_\ell$, where $\underline{r}_\ell$ solves

$$r_2 + \frac{1}{2-\gamma} - \frac{4\underline{r}_\ell}{2\underline{r}_\ell(1+\gamma)+3-\sqrt{4(1+\gamma)\underline{r}_\ell\left(\underline{r}_\ell(1+\gamma)+1\right)+9}} = 0, \tag{A.70}$$

and satisfies $\underline{r}_\ell > r_2$. Conversely, in the parameter region where (Equation A.69) does not hold, we define $\underline{r}_\ell$ to be equal to r_2, which implies that $\theta^*_{1\ell} \in (0,1)$ and $\theta^*_{2\ell}(d_3) = 0$ for all $d_3 \in [0,1]$ cannot occur in equilibrium, as $r_1 > \underline{r}_\ell$ for all r_1 by definition.

(c) Note that (Equation 2.13) and (Equation 2.12) are obtained by equating Zone 1 and Zone 2 drivers' expected utilities from staying and moving, respectively. Our approach here is as follows. We first take $\theta_{1\ell} \in (0,1)$ as given and show that a unique interior solution $\theta^*_{2\ell}(d_3)$ exists for the normalized form of (Equation 2.12), i.e.,

$$\frac{1}{(2-\gamma)(1-\theta_{2\ell}(d_3))} = \frac{d_3}{(1+\gamma)\theta_{1\ell}+(2-\gamma)\theta_{2\ell}(d_3)} - r_2, \tag{A.71}$$

if $d_3 > \bar{d}_3$, where

$$\bar{d}_3 = \frac{(1+r_2(2-\gamma))(1+\gamma)\theta_{1\ell}}{2-\gamma},$$

and $\theta^*_{2\ell}(d_3) = 0$ otherwise. We then substitute $\theta^*_{2\ell}(d_3)$ in the normalized form of (Equation 2.13), i.e.,

$$\frac{1}{(1+\gamma)(1-\theta_{1\ell})} - \left(E\left[\frac{d_3}{(1+\gamma)\theta_{1\ell}+(2-\gamma)\theta_{2\ell}(d_3)}\right] - r_1\right) = 0, \tag{A.72}$$

and show that a unique solution $\theta^*_{1\ell} \in (0,1)$ exists.

First, solving (Equation A.71) for $\theta_{2\ell}$ yields two solutions $\overline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$ and $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$ given by

$$\overline{\theta}_{2\ell}(\theta_{1\ell}, d_3) = \frac{1 + d_3 + r_2(2-\gamma-(1+\gamma)\theta_{1\ell}) + \sqrt{(r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3))^2 + 4r_2(2-\gamma+\theta_{1\ell}(1+\gamma))}}{2r_2(2-\gamma)}, \quad \text{(A.73)}$$

$$\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3) = \frac{1 + d_3 + r_2(2-\gamma-(1+\gamma)\theta_{1\ell}) - \sqrt{(r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3))^2 + 4r_2(2-\gamma+\theta_{1\ell}(1+\gamma))}}{2r_2(2-\gamma)}. \quad \text{(A.74)}$$

Consider the expression for $\overline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$ in (Equation A.73), in which the term inside the square root is strictly greater than $(r_2(2-\gamma+(1+\gamma)\theta_1) - (1+d_3))^2 \geq 0$ and is positive for all $\theta_{1\ell} \in (0,1)$ by $r_2 \in (0,1)$ and $\gamma \in [0,1]$. This helps us to identify a lower bound on $\overline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$. If $r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3) > 0$, then $\overline{\theta}_{2\ell}(\theta_{1\ell}, d_3) > 1$. If $r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3) \leq 0$, then $\overline{\theta}_{2\ell}(\theta_{1\ell}, d_3) > [(1+d_3) - r_2(1+\gamma)\theta_{1\ell}]/[r_2(2-\gamma)] \geq 1$. Thus, $\overline{\theta}_{2\ell}(\theta_{1\ell}, d_3) > 1$, and can be ruled out.

Consider the expression for $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$ in (Equation A.74). The term inside the square root is strictly greater than $(r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3))^2 \geq 0$ and is strictly positive. This helps us to identify an upper bound on $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$. If $r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3) > 0$, then $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3) < [1+d_3-(1+\gamma)r_2\theta_{1\ell}]/[r_2(2-\gamma)] < 1$. If $r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3) \leq 0$, it follows that $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3) < 1$. Furthermore, since the denominator of $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$ is positive by $r_2 > 0$ and $\gamma \in [0,1]$, $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3)$ is positive if and only if $(1+d_3+r_2(2-\gamma-(1+\gamma)\theta_{1\ell}))^2 - [(r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) - (1+d_3))^2 + 4r_2(2-\gamma+\theta_{1\ell}(1+\gamma))] > 0$, which using simple algebra is equivalent to

$$d_3 > \overline{d}_3 = \frac{(1+r_2(2-\gamma))(1+\gamma)\theta_{1\ell}}{2-\gamma}. \quad \text{(A.75)}$$

For $d_3 \leq \overline{d}_3$, the left-hand side of (Equation A.71) is greater than its right-hand side for all $\theta_{2\ell}(d_3) \geq 0$ given $\theta_{1\ell} \in (0,1)$, which implies that Zone 2 drivers would optimally choose to stay, and hence, $\theta^*_{2\ell}(d_3) = 0$. To summarize,

$$\theta^*_{2\ell}(d_3) = \begin{cases} 0, & \text{if } d_3 \leq \overline{d}_3 \\ \underline{\theta}_{2\ell}(\theta_{1\ell}, d_3), & \text{if } d_3 > \overline{d}_3. \end{cases} \tag{A.76}$$

Note also that $\overline{d}_3 < 1$ if and only if the following condition holds:

$$r_2 < \frac{1}{(1+\gamma)\theta_{1\ell}} - \frac{1}{2-\gamma}. \tag{A.77}$$

We will proceed by assuming that (Equation A.77) holds and $\overline{d}_3 < 1$, and we will verify later that this condition holds for $\theta_{1\ell} = \theta^*_{1\ell}$ and under the conditions stated in Proposition 3c.

Next, we substitute $\theta^*_{2\ell}(d_3)$ defined in (Equation A.76) into (Equation A.72), and find the condition for a unique $\theta^*_{1\ell} \in (0, 1)$ that solves (Equation 2.13). To do this, we first analyze the derivative of the left-hand side of (Equation A.72) with respect to $\theta_{1\ell}$. Note that the term $1/[(1+\gamma)(1-\theta_{1\ell})]$ in (Equation A.72) is strictly increasing in $\theta_{1\ell}$ by $\gamma \in [0, 1]$, and we can therefore focus on the term involving the expectation in (Equation A.72). Upon substituting $\theta^*_{2\ell}(d_3)$ defined in (Equation A.76) into (Equation A.72), the derivative of the expectation involved in (Equation A.72) with respect to $\theta_{1\ell}$ can be written as

$$\frac{d}{d\theta_{1\ell}}\left[\int_0^{\overline{d}_3} \frac{d_3}{(1+\gamma)\theta_{1\ell}} dd_3\right] + \frac{d}{d\theta_{1\ell}}\left[\int_{\overline{d}_3}^1 \frac{d_3}{(1+\gamma)\theta_{1\ell} + (2-\gamma)\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3)} dd_3\right]. \tag{A.78}$$

It can be verified that the derivative of the expression inside the integral in the second term of (Equation A.78) with respect to $\theta_{1\ell}$ exists for all $d_3 \in (0, 1]$ and $\theta_{1\ell} \in (0, 1)$, and the derivative of $\overline{d}_3$ defined in (Equation A.75) with respect to $\theta_{1\ell}$ also exists. Therefore, the Leibniz rule can be applied to the second term of (Equation A.78). Applying the Leibniz rule to the second term of (Equation A.78), the overall expression in (Equation A.78) evaluates to

$$\frac{(1+\gamma)(1+r_2(2-\gamma))^2}{2(2-\gamma)^2}\Big[1-$$
$$\frac{4r_2(1+\gamma)(2-\gamma)}{1+d_3+r_2(2-\gamma+(1+\gamma)\theta_{1\ell})-\sqrt{(1+d_3-r_2(2-\gamma+(1+\gamma)\theta_{1\ell}))^2+4r_2(2-\gamma+(1+\gamma)\theta_{1\ell})}}\Big]+$$
$$\int_{\bar{d}_3}^{1}\left[\frac{\partial}{\partial\theta_{1\ell}}\frac{d_3}{(1+\gamma)\theta_{1\ell}+(2-\gamma)\underline{\theta}_{2\ell}(\theta_{1\ell},d_3))}\right]dd_3. \quad \text{(A.79)}$$

We first show that the term inside the integral in (Equation A.79) is negative for each $d_3 > 0$. Note that the expression inside the square brackets in the integral is

$$\frac{-4r_2^2 d_3 \frac{1+\gamma}{2}\left[1-\frac{1-d_3+r_2(2-\gamma+(1+\gamma)\theta_{1\ell})}{\sqrt{(1-d_3+r_2(2-\gamma+(1+\gamma)\theta_{1\ell}))^2+4d_3}}\right]}{\left[-1-d_3-r_2(2-\gamma+(1+\gamma)\theta_{1\ell})+\sqrt{(1-d_3+r_2(2-\gamma+(1+\gamma)\theta_{1\ell}))^2+4d_3}\right]^2}. \quad \text{(A.80)}$$

The denominator in (Equation A.80) is positive for all $\theta_{1\ell} \in (0,1)$ and $d_3 \in (0,1]$, because $r_2 \in (0,1)$ and $\gamma \in [0,1]$. Moreover, we can show that (Equation A.80) is negative for $d_3 > 0$. To see this point, note that the term inside the square brackets in the numerator lies in $(0,1)$ because $(1-d_3+r_2(2-\gamma+(1+\gamma)\theta_{1\ell}))^2 > (1-d_3+r_2(2-\gamma+(1+\gamma)\theta_{1\ell}))^2+4d_3 > 0$ and $1-d_3+r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) > 0$ for all $\theta_{1\ell} \in (0,1)$ and $d_3 \in (0,1]$, by $r_2 \in (0,1)$ and $\gamma \in [0,1]$. Therefore, the expression inside the integral in (Equation A.79) is negative for each $d_3 > 0$ and its integral will evaluate to a negative value.

Next, we focus on the first two lines of (Equation A.79). The term outside the square brackets in the first two lines of (Equation A.79) is positive by $\gamma \in [0,1]$, and hence we can focus on the term inside the square brackets. The term inside the square root is strictly greater than $(1+d_3-r_2(2-\gamma+(1+\gamma)\theta_{1\ell}))^2$. This helps us to identify an upper bound on the expression inside the square brackets in the first two lines of (Equation A.79). If $1+d_3-r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) > 0$, the expression is strictly less than $[2-\gamma+(1+\gamma)\theta_{1\ell}-2(1+\gamma)(2-\gamma)]/[2-\gamma+(1+\gamma)\theta_{1\ell}]$, whose numerator is less than or equal to $2-\gamma+(1+\gamma)-2(1+\gamma)(2-\gamma)$, which is strictly negative for all $\theta_{1\ell} \in (0,1)$ by $\gamma \in [0,1]$. Moreover, the denominator, $2-\gamma+(1+\gamma)\theta_{1\ell}$, is strictly positive for all $\theta_{1\ell} \in (0,1)$ by $\gamma \in [0,1]$. If $1+d_3-r_2(2-\gamma+(1+\gamma)\theta_{1\ell}) \leq 0$, then the expression is strictly less than $1 - [2r_2(1+\gamma)(2-\gamma)]/[1+d_3]$, which using $1 + d_3 - r_2(2 - \gamma + (1+\gamma)\theta_{1\ell}) \leq 0$ and simple algebra is strictly less than $r_2[3 - 2(1+\gamma)(2-\gamma)]/[1+d_3]$, which is strictly negative by $r_2 \in (0,1)$, $d_3 \in (0,1]$, and $\gamma \in [0,1]$. Thus, the expression in (Equation A.79) is strictly negative. This implies that the left-hand side of (Equation A.72) is strictly increasing in $\theta_{1\ell}$ for $\theta_{1\ell} \in (0,1)$.

Next, we show that the left-hand side of (Equation A.72) evaluated at $\theta_{1\ell} = \theta_{1\ell,1}$ is positive, where $\theta_{1\ell,1}$ is defined in (Equation A.65) in the proof of Proposition 3b. Evaluating the left-hand side of (Equation A.72) at $\theta_{1\ell} = \theta_{1\ell,1}$ leads to

$$\frac{1}{(1+\gamma)(1-\theta_{1\ell,1})} - \int_0^{\overline{d}_3} \frac{d_3}{(1+\gamma)\theta_{1\ell,1}} dd_3 - \int_{\overline{d}_3}^{1} \frac{d_3}{(1+\gamma)\theta_{1\ell,1} + (2-\gamma)\underline{\theta}_{2\ell}(\theta_{1\ell,1}, d_3)} dd_3 + r_1. \tag{A.81}$$

Note that $\theta_{1\ell,1}$ satisfies (Equation A.64) and $\underline{\theta}_{2\ell}(\theta_{1\ell}, d_3) > 0$ for all $d_3 > \overline{d}_3$, and hence (Equation A.81) evaluates to a non-negative value if $\overline{d}_3$, which is defined in (Equation A.75) evaluates to a value less than 1 at $\theta_{1\ell} = \theta_{1\ell,1}$. This is equivalent to

$$r_2 < \frac{1}{(1+\gamma)\theta_{1\ell,1}} - \frac{1}{2-\gamma}. \tag{A.82}$$

By algebra, it can be shown that (Equation A.82) is the opposite of (Equation A.68), as established in the proof of Proposition 3b, and is equivalent to $r_1 > \underline{r}_\ell$. To summarize, since the left-hand side of (Equation A.72) evaluated at $\theta_{1\ell} = \theta_{1\ell,1}$ is positive and the left-hand side of (Equation A.72) is strictly increasing in $\theta_{1\ell}$, the equilibrium $\theta^*_{1\ell}$, if it exists, will be less than $\theta_{1\ell,1}$. Since $\theta_{1\ell,1} < 1$ as established in the proof of Proposition 3b, it follows that $\theta^*_{1\ell} < 1$. Furthermore, $\theta^*_{1\ell}$, if it exists, is unique since the left-hand side of (Equation A.72) is strictly increasing in $\theta_{1\ell}$.

Finally, it remains to be shown that the left-hand side of (Equation A.72) evaluated at $\theta_{1\ell} = 0$ is negative, which by Intermediate Value Theorem guarantees that a solution $\theta^*_{1\ell}$ to (Equation A.72) exists. Note that $\overline{d}_3$ defined in (Equation A.75) at $\theta_{1\ell} = 0$ equals 0 and $\theta^*_{2\ell}(d_3)$ defined in (Equation A.76), at $\theta_{1\ell} = 0$, is equivalent to $\theta_{2\ell,1}(d_3)$ defined in (Equation A.59) in the proof of Proposition 3a. Thus, the left-hand side of (Equation A.72) evaluated at $\theta_{1\ell} = 0$ is negative if and only if

$$\frac{1}{(1+\gamma)} - E\left[\frac{d_3}{(2-\gamma)\theta^*_{2\ell}(d_3)}\right] + r_1 = \frac{1}{(1+\gamma)} - E\left[\frac{d_3}{(2-\gamma)\theta_{2\ell,1}(d_3)}\right] + r_1 < 0. \tag{A.83}$$

This condition is the opposite of $r_1 \geq \overline{r}_\ell$, as established in the proof of Proposition 3a, and is equivalent to $r_1 < \overline{r}_\ell$.

Supplementary Analytical Results

Proposition 4. *With full information sharing, there exist thresholds for* $d_1 > 0, d_2 = 0, d_3 > 0$ *such that*

(a) an equilibrium exists in which only some or all drivers initially in Zone 2 relocate to Zone 3 if and only if $r_1 \geq \max\{r_2, \frac{pd_3}{n(2-\gamma)}\} - \frac{2pd_1}{n(1+\gamma)}$. *In this equilibrium,* $\theta^*_{1f}(d_1, d_2, d_3) = 0$ *and* $\theta^*_{2f}(d_1, d_2, d_3) = \min\{\frac{pd_3}{nr_2(2-\gamma)}, 1\} \in (0, 1]$.

(b) An equilibrium exists in which some drivers initially in Zone 1 and all drivers initially in Zone 2 relocate to Zone 3 if and only if $r_1 < \frac{pd_3}{n(2-\gamma)} - \frac{2pd_1}{n(1+\gamma)}$. *In this equilibrium,* $\theta^*_{2f}(d_1, d_2, d_3) = 1$ *and*

$$\theta^*_{1f}(d_1, d_2, d_3) = \frac{p\left(2d_1 + d_3 - n\sqrt{\frac{(2d_1+d_3)^2}{n^2} + \frac{6(2d_1-d_3)r_1}{np} + \frac{9r_1^2}{p^2}}\right) + (2\gamma - 1)nr_1}{2(1+\gamma)nr_1} \in (0, 1). \tag{A.84}$$

Proof of Proposition 4 To simplify the presentation of the proof, we continue to use notation in the normalized form.

First, we show that when $d_3 = 0$, a unique equilibrium exists in which $\theta^*_{1f} = \theta^*_{2f} = 0$. Note that if $d_3 = 0$, the expected earnings from moving given by (Equation A.6) and (Equation A.8) for drivers in Zones 1 and 2, respectively, are strictly negative because $r_1, r_2 > 0$. The expected earnings from staying, given by (Equation A.5) and (Equation A.7) for drivers in Zones 1 and 2, respectively, are greater than or equal to 0 for any $\theta^*_{1f}, \theta^*_{2f} \in [0, 1)$ by $\gamma \in [0, 1]$ and $\{d_1, d_2\} \geq 0$.

Since the expected earnings from staying dominate those from moving for drivers in Zones 1 and 2, it follows that $\theta^*_{1f} = \theta^*_{2f} = 0$ when $d_3 = 0$.

The rest of the proof focuses on the case $d_3 > 0$.

(a) It follows similarly to the proof of Proposition 2a that Zone 1 drivers do not move in equilibrium if and only if

$$r_1 \geq \frac{d_3}{(2-\gamma)\theta^*_{2f}} - \frac{2d_1}{1+\gamma}, \tag{A.85}$$

where θ^*_{2f} equals 1 if $r_2 \leq d_3/(2-\gamma)$ (meaning that Zone 2 drivers' expected earnings from moving dominate those from staying for $\theta^*_{2f} = 1$ and hence all Zone 2 drivers move), and otherwise, θ^*_{2f} is obtained by solving

$$0 = \frac{d_3}{(2-\gamma)\theta^*_{2f}} - r_2, \tag{A.86}$$

which leads to $\theta^*_{2f} = d_3/[r_2(2-\gamma)]$. Note that $r_2 > d_3/(2-\gamma)$ implies that $\theta^*_{2f} < 1$, and $d_3 > 0$, $r_2 > 0$, and $\gamma \in [0, 1]$ imply that $\theta^*_{2f} > 0$. Substituting θ^*_{2f} in (Equation A.85), (Equation A.85) is equivalent to $r_1 \geq \frac{d_3}{2-\gamma} - \frac{2d_1}{1+\gamma}$ if $r_2 \leq d_3/(2-\gamma)$, and is equivalent to $r_1 \geq r_2 - \frac{2d_1}{1+\gamma}$ otherwise. In our original notation, the condition on r_1 can be summarized as $r_1 \geq \max\{r_2, pd_3/[n(2-\gamma)]\} - 2pd_1/[n(1+\gamma)]$.

(b) All Zone 2 drivers move in equilibrium if and only if, given θ^*_{1f}, i.e., the proportion of Zone 1 drivers that move, their expected earnings from moving are greater than or equal to those from staying for $\theta^*_{2f} = 1$. It follows from (Equation A.7) and (Equation A.8) that all Zone 2 drivers move if and only if

$$r_2 \leq \frac{d_3}{2-\gamma+(1+\gamma)\theta^*_{1f}}. \tag{A.87}$$

At the equilibrium proportion θ^*_{1f}, by definition, Zone 1 drivers are indifferent between staying and moving given $\theta^*_{2f} = 1$. It follows from (Equation A.5) and (Equation A.6) that θ^*_{1f} is obtained by solving

$$r_1 - \frac{d_3}{2-\gamma+(1+\gamma)\theta^*_{1f}} + \frac{2d_1}{(1+\gamma)(1-\theta^*_{1f})} = 0. \tag{A.88}$$

We obtain two solutions

$$\tilde{\theta}_{1f,1} = \frac{2d_1 + d_3 + (2\gamma - 1)r_1 - \sqrt{(2d_1 + 3r_1)^2 + d_3^2 + 4d_1 d_3 - 6d_3 r_1}}{2(1+\gamma)r_1}, \tag{A.89}$$

$$\tilde{\theta}_{1f,2} = \frac{2d_1 + d_3 + (2\gamma - 1)r_1 + \sqrt{(2d_1 + 3r_1)^2 + d_3^2 + 4d_1 d_3 - 6d_3 r_1}}{2(1+\gamma)r_1}. \tag{A.90}$$

Consider $\tilde{\theta}_{1f,2}$ in (Equation A.90). The term inside the square root can be rewritten as $(3r_1 + 2d_1 - d_3)^2 + 8d_1 d_3$, which is strictly greater than $(3r_1 + 2d_1 - d_3)^2 \geq 0$ and is strictly positive by $\{d_1, d_3\} > 0$. Next, we show that $\tilde{\theta}_{1f,2} > 1$. Note that

$$\tilde{\theta}_{1f,2} - 1 = \frac{2d_1 + d_3 - 3r_1 + \sqrt{(2d_1 + 3r_1)^2 + d_3^2 + 4d_1 d_3 - 6d_3 r_1}}{2(1+\gamma)r_1},$$

where the denominator is positive by $r_1 \in (0, 1)$ and $\gamma \in [0, 1]$. If $2d_1 + d_3 - 3r_1 > 0$, then $\tilde{\theta}_{1f,2} > 1$. If $2d_1 + d_3 - 3r_1 \leq 0$, then the numerator is positive if and only if $(2d_1 + d_3 - 3r_1)^2 < (2d_1 + 3r_1)^2 + d_3^2 + 4d_1 d_3 - 6d_3 r_1$, which by algebra is equivalent to $-24r_1 d_1 < 0$, and is true due to $d_1 > 0$ and $r_1 > 0$. Therefore, $\tilde{\theta}_{1f,2} > 1$ and can be omitted.

Consider $\tilde{\theta}_{1f,1}$ in (Equation A.89). The term inside the square root is positive as shown above. Next, we show that $\tilde{\theta}_{1f,1} < 1$. Note that

$$\tilde{\theta}_{1f,1} - 1 = \frac{2d_1 + d_3 - 3r_1 - \sqrt{(2d_1 + 3r_1)^2 + d_3^2 + 4d_1 d_3 - 6d_3 r_1}}{2(1+\gamma)r_1},$$

where the denominator is positive by $r_1 \in (0, 1)$ and $\gamma \in [0, 1]$. If $2d_1 + d_3 - 3r_1 \leq 0$, it follows that $\tilde{\theta}_{1f,1} < 1$. If $2d_1 + d_3 - 3r_1 > 0$, it follows from $(2d_1 + d_3 - 3r_1)^2 < (2d_1 + 3r_1)^2 + d_3^2 + 4d_1 d_3 - 6d_3 r_1$, as shown above, that $\tilde{\theta}_{1f,1} < 1$. Next, we identify the condition for $\tilde{\theta}_{1f,1} > 0$. Since the denominator and the term inside the square root in (Equation A.89) are positive, $\tilde{\theta}_{1f,1} > 0$ if and only if $(2d_1 + d_3 + (2\gamma - 1)r_1)^2 > (2d_1 + 3r_1)^2 + d_3^2 + 4d_1 d_3 - 6d_3 r_1$, which by algebra is equivalent to $r_1 < d_3/(2 - \gamma) - 2d_1/(1 + \gamma)$. Consequently, a unique solution $\theta^*_{1f} \in (0, 1)$ exists in the region $r_1 < d_3/(2 - \gamma) - 2d_1/(1 + \gamma)$, and is equal to $\tilde{\theta}_{1f,1}$. Substituting $\theta^*_{1f} = \tilde{\theta}_{1f,1}$ in

(Equation A.87), (Equation A.87) is equivalent to

$$r_2 \leq \frac{d_3}{2-\gamma+(1+\gamma)\tilde{\theta}_{1f,1}}. \tag{A.91}$$

Since $\tilde{\theta}_{1f,1}$ solves (Equation A.88), it follows that $d_3/[(2-\gamma)+(1+\gamma)\tilde{\theta}_{1f,1}] = r_1+2d_1/[(1+\gamma)\tilde{\theta}_{1f,1}]$, and hence (Equation A.91) can be rewritten as

$$r_2 \leq r_1 + \frac{2d_1}{(1+\gamma)(1-\tilde{\theta}_{1f,1})}. \tag{A.92}$$

Given that $r_1 < r_1+2d_1/[(1+\gamma)(1-\tilde{\theta}_{1f,1})]$ in the region $r_1 < d_3/(2-\gamma)-2d_1/(1+\gamma)$ due to $d_1 > 0$, $\gamma \in [0,1]$, and $\tilde{\theta}_{1f,1} \in (0,1)$, (Equation A.92) holds in the region $r_1 < d_3/(2-\gamma)-2d_1/(1+\gamma)$ by the assumption that $r_2 < r_1$.

Finally, $r_2 \leq d_3/(2-\gamma)$ is satisfied in the region $r_1 < d_3/(2-\gamma)-2d_1/(1+\gamma)$ because $d_3/(2-\gamma)-2d_1/(1+\gamma) < d_3/(2-\gamma)$ by $d_1 > 0$ and $\gamma \geq 0$. Given $r_2 \leq d_3/(2-\gamma)$, the condition $r_1 < d_3/(2-\gamma)-2d_1/(1+\gamma)$ is the opposite of the condition in Proposition 4a.

Proposition 5. *With full information sharing, there exist thresholds for $d_1 = 0, d_2 > 0, d_3 > 0$ such that*

(a) an equilibrium exists in which only some drivers initially in Zone 2 relocate to Zone 3 if and only if $r_1 \geq \overline{r}_f$. In this equilibrium, $\theta^*_{1f}(d_1,d_2,d_3) = 0$ and

$$\theta^*_{2f}(d_1,d_2,d_3) = \\ \frac{(2d_2+d_3)\,p+(2-\gamma)nr_2-\sqrt{(2d_2p+d_3p+(2-\gamma)nr_2)^{\,2}-4(2-\gamma)d_3npr_2}}{2(2-\gamma)nr_2} \in (0,1). \tag{A.93}$$

(b) An equilibrium exists in which only some or all drivers initially in Zone 1 relocate to Zone 3 if and only if $r_1 \leq \underline{r}_f$ and $r_2 \geq \frac{pd_3}{n(1+\gamma)} - \frac{2pd_2}{n(2-\gamma)}$. In this equilibrium, $\theta^*_{1f}(d_1,d_2,d_3) = \min\{\frac{pd_3}{nr_1(1+\gamma)}, 1\} \in (0,1]$ and $\theta^*_{2f}(d_1,d_2,d_3) = 0$.

(c) *An equilibrium exists in which all drivers initially in Zone 1 and some drivers initially in Zone 2 relocate to Zone 3 if and only if* $r_1 \leq \underline{r}_f^1$ *and* $r_2 < \frac{pd_3}{n(1+\gamma)} - \frac{2pd_2}{n(2-\gamma)}$. *In this equilibrium,* $\theta_{1f}^*(d_1, d_2, d_3) = 1$ *and*

$$\theta_{2f}^*(d_1, d_2, d_3) = \frac{(2d_2 + d_3)\,p - (2\gamma - 1)nr_2 - \sqrt{4d_2p\,(d_3p + 3nr_2) + (d_3p - 3nr_2)^{\,2} + 4d_2^2p^2}}{2(2-\gamma)nr_2} \in (0,1). \tag{A.94}$$

(d) *If* $\underline{r}_f < r_1 < \overline{r}_f$ *and* $r_2 \geq \frac{pd_3}{n(1+\gamma)} - \frac{2pd_2}{n(2-\gamma)}$, *or* $\underline{r}_f^1 < r_1 < \overline{r}_f$ *and* $r_2 < \frac{pd_3}{n(1+\gamma)} - \frac{2pd_2}{n(2-\gamma)}$, *a unique equilibrium exists in which some drivers initially in Zones 1 and 2 relocate to Zone 3. In this equilibrium,*

$$\theta_{1f}^*(d_1, d_2, d_3) = \frac{\frac{d_3p}{r_1} + \frac{2d_2p}{r_1 - r_2} - (2-\gamma)n}{(1+\gamma)n} \in (0,1), \tag{A.95}$$

$$\theta_{2f}^*(d_1, d_2, d_3) = 1 - \frac{2d_2p}{(2-\gamma)n\,(r_1 - r_2)} \in (0,1). \tag{A.96}$$

Proof of Proposition 5 To simplify the presentation of the proof, we continue to use notation in the normalized form.

(a) It follows similarly to the proof of Proposition 2a that Zone 1 drivers do not move in equilibrium given θ_{2f}^* if and only if

$$r_1 \geq \frac{d_3}{(2-\gamma)\theta_{2f}^*}, \tag{A.97}$$

where θ_{2f}^* is obtained by solving

$$\frac{2d_2}{(2-\gamma)(1-\theta_{2f}^*)} = \frac{d_3}{(2-\gamma)\theta_{2f}^*} - r_2. \tag{A.98}$$

We obtain two solutions $\theta_{2f,1}$ and $\theta_{2f,2}$ defined in (Equation A.38) and (Equation A.39), respectively, in the proof of Proposition 2a. It follows from the two paragraphs below (Equation A.39) in the proof of Proposition 2a that $\theta_{2f,1} \in (0,1)$, and $\theta_{2f,2} > 1$ can be omitted. Consequently, a unique internal solution θ^*_{2f} exists, and is equal to $\theta_{2f,1}$. The threshold $\overline{r}_f$ is found by substituting $\theta^*_{2f} = \theta_{2f,1}$ on the right-hand side of (Equation A.97), which gives

$$r_1 \geq \overline{r}_f = \frac{d_3}{(2-\gamma)\theta_{2f,1}}. \tag{A.99}$$

In our original notation, $\overline{r}_f$ is equivalent to

$$\overline{r}_f = \frac{2}{n^2}\left(\frac{d_3 n^2 p r_2}{(2d_2+d_3)\,p^2 + (2-\gamma)n^2 r_2 - np\sqrt{\left(\frac{(2d_2+d_3)p}{n} + \frac{(2-\gamma)nr_2}{p}\right)^2 - 4(2-\gamma)d_3 r_2}}\right). \tag{A.100}$$

(b) It follows similarly to the proof of Proposition 2b that Zone 2 drivers do not move in equilibrium given θ^*_{1f} if and only if

$$r_2 \geq \frac{d_3}{(1+\gamma)\theta^*_{1f}} - \frac{2d_2}{2-\gamma}, \tag{A.101}$$

where θ^*_{1f} equals 1 if $r_1 \leq d_3/(1+\gamma)$ (meaning that Zone 1 drivers' expected earnings from moving dominate those from staying for $\theta^*_{1f} = 1$ and hence all Zone 1 drivers move), and otherwise, θ^*_{1f} is obtained by solving

$$0 = \frac{d_3}{(1+\gamma)\theta^*_{1f}} - r_1, \tag{A.102}$$

which leads to $\theta^*_{1f} = d_3/[r_1(1+\gamma)]$. Note that $r_1 > d_3/(1+\gamma)$ implies that $\theta^*_{1f} < 1$, and $d_3 > 0$, $r_1 > 0$, and $\gamma \in [0,1]$ imply that $\theta^*_{1f} > 0$. Substituting θ^*_{1f} in (Equation A.101), (Equation A.101) is equivalent to $r_2 \geq \frac{d_3}{1+\gamma} - \frac{2d_2}{2-\gamma}$ if $r_1 \leq d_3/(1+\gamma)$, and is equivalent to $r_2 \geq r_1 - \frac{2d_2}{1-\gamma}$ otherwise. Therefore, (Equation A.101) can be summarized as

$$r_2 \geq \max\left\{r_1, \frac{d_3}{1+\gamma}\right\} - \frac{2d_2}{2-\gamma}. \tag{A.103}$$

This parameter region can equivalently be characterized as $r_2 \geq d_3/(1+\gamma) - 2d_2/(2-\gamma)$ and $r_1 \leq \underline{r}_f = r_2 + 2d_2/(2-\gamma)$. In our original notation, $\underline{r}_f$ is equivalent to $\underline{r}_f = r_2 + 2pd_2/[n(2-\gamma)]$.

(c) It follows from (Equation A.5) and (Equation A.6) that all Zone 1 drivers move in equilibrium given θ^*_{2f} if and only if

$$r_1 \leq \frac{d_3}{1+\gamma+(2-\gamma)\theta^*_{2f}}, \tag{A.104}$$

where θ^*_{2f} solves

$$\frac{2d_2}{(2-\gamma)(1-\theta^*_{2f})} = \frac{d_3}{1+\gamma+(2-\gamma)\theta^*_{2f}} - r_2. \tag{A.105}$$

We obtain two solutions

$$\bar{\theta}_{2,1} = \frac{2d_2 + d_3 - 2\gamma r_2 + r_2 - \sqrt{(3r_2+2d_2-d_3)^2 + 8d_2d_3}}{2(2-\gamma)r_2}, \tag{A.106}$$

$$\bar{\theta}_{2,2} = \frac{2d_2 + d_3 - 2\gamma r_2 + r_2 + \sqrt{(3r_2+2d_2-d_3)^2 + 8d_2d_3}}{2(2-\gamma)r_2}. \tag{A.107}$$

Consider $\bar{\theta}_{2,2}$ in (Equation A.107). The term inside the square root is greater than $(3r_2 + 2d_2 - d_3)^2 \geq 0$ and is positive by $\{d_2, d_3\} > 0$, which helps us to find a lower bound on $\bar{\theta}_{2,2}$. If $3r_2 + 2d_2 - d_3 \geq 0$, then $\bar{\theta}_{2,2} > [4r_2 + 4d_2 - 2r_2\gamma]/[4r_2 - 2r_2\gamma] > 1$ due to $d_2 > 0$, $r_2 > 0$, and $\gamma \geq 0$. If $3r_2 + 2d_2 - d_3 < 0$, then $\bar{\theta}_{2,2} > [2d_3 - 2r_2 - 2r_2\gamma]/[4r_2 - 2r_2\gamma]$, which is strictly greater than 1 due to $3r_2 - d_3 < -2d_2 < 0$ by $d_2 > 0$. Therefore, $\bar{\theta}_{2,2} > 1$ and can be omitted.

Consider $\bar{\theta}_{2,1}$ in (Equation A.106). Since the term inside the square root is positive as shown above, $\bar{\theta}_{2,1} > 0$ requires $2d_2 + d_3 + r_2(1-2\gamma) > 0$, which by algebra is equivalent to $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$. Furthermore, if $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$, then $\bar{\theta}_{2,1} < 1$ is equivalent to $(2d_2 + d_3 - 3r_2)^2 < (3r_2 + 2d_2 - d_3)^2 + 8d_2d_3$, which by simple algebra simplifies to $-24r_2d_3 + (-1+d_3)d_3 < 0$ and holds due to $r_2 \in (0,1)$ and $d_3 \in (0,1]$. Therefore, a unique internal solution θ^*_{2f} exists in the region $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$, and is equal to $\bar{\theta}_{2,1}$. Substituting $\theta^*_{2f} = \bar{\theta}_{2,1}$ in (Equation A.104), (Equation A.104) is equivalent to

$$r_1 \leq \underline{r}^1_f = \frac{d_3}{1+\gamma+(2-\gamma)\bar{\theta}_{2,1}}. \tag{A.108}$$

Finally, note that the threshold $\underline{r}^1_f$ is less than $d_3/(1+\gamma)$ for $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$ by $d_3 > 0$, $\gamma \in [0,1]$, and $\bar{\theta}_{2,1} \in (0,1)$, and does not overlap with the region characterized in

Proposition 5b. In our original notation, $\underline{r}_f^1$ is equivalent to

$$\underline{r}_f^1 = \frac{2d_3 r_2}{p\left(2d_2 + d_3 - n\sqrt{\frac{(2d_2+d_3)^2}{n^2} + \frac{6(2d_2-d_3)r_2}{np} + \frac{9r_2^2}{p^2}}\right) + 3nr_2}. \tag{A.109}$$

(d) By definition, drivers in Zones 1 and 2 are indifferent between staying and moving at equilibrium θ_{1f}^* and θ_{2f}^*. It follows from solving (Equation 2.7) and (Equation 2.8) for $d_1 = 0$ that

$$\theta_{1f}^* = 1 + \frac{r_1\left(2d_2 + d_3 + 3r_2\right) - d_3 r_2 - 3r_1^2}{(1+\gamma)r_1\left(r_1 - r_2\right)}, \tag{A.110}$$

$$\theta_{2f}^* = 1 - \frac{2d_2}{(2-\gamma)\left(r_1 - r_2\right)}. \tag{A.111}$$

We show that θ_{1f}^* and θ_{2f}^* characterized in (Equation A.110) and (Equation A.111), respectively, are such that $\theta_{1f}^* \in (0,1)$ and $\theta_{2f}^* \in (0,1)$ under the conditions given in Proposition 5d. To do this, we adopt a similar approach as in the proof of Proposition 2c. We show that θ_{1f} as a function of θ_{2f}, obtained as solutions for (Equation 2.7) and (Equation 2.8) separately, intersect exactly once for $\theta_{1f} \in (0,1)$ and $\theta_{2f} \in (0,1)$ under the conditions given in Proposition 5d.

First, we use (Equation 2.7) and (Equation 2.8) separately to obtain the function $\theta_{1f}(\theta_{2f})$. We obtain

$$\underline{\theta}_{1f,1}(\theta_{2f}) = \frac{d_3 - (2-\gamma)\theta_{2f} r_1}{(1+\gamma)r_1}, \tag{A.112}$$

$$\theta_{1f,2}(\theta_{2f}) = \frac{(2-\gamma)((1-\theta_{2f})(d_3 - (2-\gamma)\theta_{2f} r_2) - 2d_2\theta_{2f})}{(1+\gamma)(2d_2 + (2-\gamma)(1-\theta_{2f})r_2)}, \tag{A.113}$$

respectively. In order to characterize the conditions under which $\underline{\theta}_{1f,1}(\theta_{2f})$ and $\theta_{1f,2}(\theta_{2f})$ intersect, we first evaluate their derivatives, $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}$ and $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}$, given by

$$\frac{d\underline{\theta}_{1f,1}(\theta_{2f})}{d\theta_{2f}} = -\frac{2-\gamma}{1+\gamma}, \tag{A.114}$$

$$\frac{d\theta_{1f,2}(\theta_{2f})}{d\theta_{2f}} = -\frac{2-\gamma}{1+\gamma} - \frac{2(2-\gamma)d_2 d_3}{(1+\gamma)(2d_2 + r_2(2-\gamma)(1-\theta_{2f}))^2}, \tag{A.115}$$

and show that they are both negative.

Firstly, $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f} < 0$ by $\gamma \in [0,1]$. Next, consider $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}$ in (Equation A.115). The first term is negative by $\gamma \in [0,1]$. In the second term, the denominator is strictly positive for all $\theta_{2f} \in (0,1)$ by $r_2 \in (0,1)$, $\gamma \in [0,1]$, and $d_2 \in (0,1]$, and the numerator is positive by $\{d_2, d_3\} \in (0,1]$ and $\gamma \in [0,1]$, which leads to $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f} < 0$.

Finally, it follows from the work shown above for $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}$ and by $\gamma \in [0,1]$ that

$$\left|\frac{d\theta_{1f,2}(\theta_{2f})}{d\theta_{2f}}\right| - \left|\frac{d\underline{\theta}_{1f,1}(\theta_{2f})}{d\theta_{2f}}\right| = \frac{2(2-\gamma)d_2 d_3}{(1+\gamma)(2d_2 + r_2(2-\gamma)(1-\theta_{2f}))^2} > 0,$$

which implies that $\theta_{1f,2}$ declines faster in θ_{2f} than $\underline{\theta}_{1f,1}$.

Since $d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f} < 0$, $d\theta_{1f,2}(\theta_{2f})/d\theta_{2f} < 0$, and $|d\theta_{1f,2}(\theta_{2f})/d\theta_{2f}| - |d\underline{\theta}_{1f,1}(\theta_{2f})/d\theta_{2f}| > 0$, the functions $\underline{\theta}_{1f,1}(\theta_{2f})$ and $\theta_{1f,2}(\theta_{2f})$ will intersect exactly once in $\theta_{1f} \in (0,1)$ and $\theta_{2f} \in (0,1)$ if one of the following two sets of conditions hold:

(i) $\underline{\theta}_{1f,1}(0) \in (0,1)$, $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0)$, and $\hat{\theta}_{2f} < \tilde{\theta}_{2f}$, where $\hat{\theta}_{2f} \in (0,1)$ and $\tilde{\theta}_{2f}$ are such that $\theta_{1f,2}(\hat{\theta}_{2f}) = 0$ and $\underline{\theta}_{1f,1}(\tilde{\theta}_{2f}) = 0$.

(ii) $\underline{\theta}_{1f,1}(0) \geq 1$, $0 < \underline{\theta}_{2f} < \bar{\theta}_{2f}$, where $\underline{\theta}_{2f}$ and $\bar{\theta}_{2f} \in (0,1)$ are such that $\underline{\theta}_{1f,1}(\underline{\theta}_{2f}) = 1$ and $\theta_{1f,2}(\bar{\theta}_{2f}) = 1$, and $\hat{\theta}_{2f} < \tilde{\theta}_{2f}$, where $\hat{\theta}_{2f} \in (0,1)$ and $\tilde{\theta}_{2f}$ are such that $\theta_{1f,2}(\hat{\theta}_{2f}) = 0$ and $\underline{\theta}_{1f,1}(\tilde{\theta}_{2f}) = 0$.

In the next few paragraphs, we characterize these two sets of conditions.

First, we consider the conditions for $\underline{\theta}_{1f,1}(0) \in (0,1)$ and $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0)$ in the first set of conditions described above. Note that $\underline{\theta}_{1f,1}(0) = d_3/[r_1(1+\gamma)]$ and $\theta_{1f,2}(0) = [(2-\gamma)d_3]/[(1+\gamma)\,(2d_2 + r_2(2-\gamma))]$. Firstly, $\underline{\theta}_{1f,1}(0) > 0$ holds by $d_3 \in (0,1]$, $r_1 \in (0,1)$, and $\gamma \in [0,1]$, and $\underline{\theta}_{1f,1}(0) < 1$ holds if $r_1 > d_3/(1+\gamma)$.

Next, we evaluate the condition for $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0)$ under $r_1 > d_3/(1+\gamma)$. $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0) < 1$ is equivalent to $d_3/(1+\gamma) - 2d_2/(2-\gamma) < r_2 < r_1 - 2d_2/(2-\gamma)$. Secondly, $\underline{\theta}_{1f,1}(0) < 1 < \theta_{1f,2}(0)$ is equivalent to $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$. Therefore, the condition $r_2 < r_1 - 2d_2/(2-\gamma)$ is sufficient for $\underline{\theta}_{1f,1}(0) < \theta_{1f,2}(0)$ under $r_1 > d_3/(1+\gamma)$, and is the opposite of the condition in Proposition 5b under $r_1 > d_3/(1+\gamma)$.

Next, we consider the conditions $\underline{\theta}_{1f,1}(0) \geq 1$ and $0 < \underline{\theta}_{2f} < \bar{\theta}_{2f}$ in the second set of conditions described above. Note that $\underline{\theta}_{1f,1}(0) \geq 1$ is equivalent to $r_1 \leq d_3/(1+\gamma)$. Moreover, $\underline{\theta}_{2f} = [d_3 - r_1(1+\gamma)]/[r_1(2-\gamma)] > 0$ is implied by $r_1 \leq d_3/(1+\gamma)$. The condition for $\underline{\theta}_{2f} < \bar{\theta}_{2f}$ is given by $r_1 > d_3/[1+\gamma+(2-\gamma)\bar{\theta}_{2f}]$, where $\bar{\theta}_{2f}$ solves $\theta_{1f,2}(\bar{\theta}_{2f}) = 1$. We obtain two solutions $\bar{\theta}_{2,1}$ and $\bar{\theta}_{2,2}$, as characterized in (Equation A.106) and (Equation A.107), respectively. Then, it follows from the two paragraphs below (Equation A.107) in the proof of Proposition 5c that $\bar{\theta}_{2f} = \bar{\theta}_{2,1} \in (0,1)$ if and only if $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$, while $\bar{\theta}_{2,2} > 1$ can be omitted. Note that the condition that ensures that $\bar{\theta}_{2f} = \bar{\theta}_{2,1} \in (0,1)$, given by $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$ is the opposite of the condition in Proposition 5b under $r_1 \leq d_3/(1+\gamma)$.

It follows that the condition $0 < \underline{\theta}_{2f} < \bar{\theta}_{2f}$ is equivalently characterized by $r_1 > \underline{r}_f^1 = d_3/[1+\gamma+(2-\gamma)\bar{\theta}_{2,1}]$ and $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$, and is the opposite of the condition in Proposition 5c under $r_2 < d_3/(1+\gamma) - 2d_2/(2-\gamma)$.

To summarize, if $r_2 \geq d_3/(1+\gamma) - 2d_2/(1+\gamma)$, then the lower threshold on r_1 for $\underline{\theta}_{1f,1}(\theta_{2f})$ and $\theta_{1f,2}(\theta_{2f})$ to intersect at interior values is given by $r_1 > \underline{r}_f$, whereas if $r_2 < d_3/(1+\gamma) - 2d_2/(1+\gamma)$, then the lower threshold on r_1 is given by $r_1 > \underline{r}_f^1$.

Next, we examine the condition $\hat{\theta}_{2f} < \tilde{\theta}_{2f}$, where $\hat{\theta}_{2f}$ and $\tilde{\theta}_{2f}$ satisfy $\theta_{1f,2}(\hat{\theta}_{2f}) = 0$ and $\underline{\theta}_{1f,1}(\tilde{\theta}_{2f}) = 0$. Note that the solutions to the equation $\theta_{1f,2}(\hat{\theta}_{2f}) = 0$, $\hat{\theta}_{2f,1}$ and $\hat{\theta}_{2f,2}$ are equivalent to $\theta_{2f,1}$ and $\theta_{2f,2}$ characterized in (Equation A.38) and (Equation A.39), respectively, in the proof of Proposition 2a. Then, it follows from the two paragraphs below (Equation A.39) in the proof of Proposition 2a that $\hat{\theta}_{2f,1} \in (0,1)$, while $\hat{\theta}_{2f,2} > 1$ can be omitted.

Furthermore, the solution to $\underline{\theta}_{1f,1}(\tilde{\theta}_{2f}) = 0$ equals $\tilde{\theta}_{2f} = d_3/[r_1(2-\gamma)]$. It follows from $d_3 \in (0,1]$, $r_1 \in (0,1)$, and $\gamma \in [0,1]$ that $\tilde{\theta}_{2f} > 0$. Lastly, we can show by algebra that the condition $\hat{\theta}_{2f,1} < \tilde{\theta}_{2f}$ is equivalent to $r_1 < d_3/[(2-\gamma)\theta_{2f,1}]$, where $\theta_{2f,1}$ is defined in (Equation A.38). This condition is the opposite of (Equation A.99) in Proposition 5a, and is equivalent to $r_1 < \bar{r}_f$.

To summarize, if $r_2 \geq d_3/(1+\gamma) - 2d_2/(1+\gamma)$, then a unique interior equilibrium exists if $\underline{r}_f < r_1 < \bar{r}_f$, whereas if $r_2 < d_3/(1+\gamma) - 2d_2/(1+\gamma)$, then a unique interior equilibrium exists if $\underline{r}_f^1 < r_1 < \overline{r}_f$.

Proposition 6. *With full information sharing, there exist thresholds for* $d_1 = 0, d_2 = 0, d_3 > 0$ *such that*

(a) an equilibrium exists in which only some or all drivers initially in Zone 2 relocate to Zone 3 if and only if $r_1 \geq pd_3/[n(2-\gamma)]$. *In this equilibrium,* $\theta^*_{1f}(d_1, d_2, d_3) = 0$ *and* $\theta^*_{2f}(d_1, d_2, d_3) = \min\{1, \frac{pd_3}{nr_2(2-\gamma)}\} \in (0, 1]$.

(b) An equilibrium exists in which all drivers relocate to Zone 3 if and only if $r_1 \leq pd_3/3n$. *In this equilibrium,* $\theta^*_{1f}(d_1, d_2, d_3) = 1$ *and* $\theta^*_{2f}(d_1, d_2, d_3) = 1$.

(c) If $pd_3/3n < r_1 < pd_3/[n(2-\gamma)]$*, a unique equilibrium exists in which a proportion of drivers initially in Zone 1 and all drivers initially in Zone 2 relocate to Zone 3. In this equilibrium,* $\theta^*_{1f}(d_1, d_2, d_3) = \frac{pd_3 - nr_1(2-\gamma)}{nr_1(1+\gamma)} \in (0, 1)$ *and* $\theta^*_{2f}(d_1, d_2, d_3) = 1$.

Proof of Proposition 6 To simplify the presentation of the proof, we continue to use notation in the normalized form.

(a) Zone 1 drivers do not move in equilibrium if and only if, given θ^*_{2f}, i.e., the equilibrium proportion of Zone 2 drivers that move, their expected earnings from staying are greater than or equal to those from moving for $\theta^*_{1f} = 0$. It follows from (Equation A.5) and (Equation A.6) that Zone 1 drivers do not move in equilibrium if and only if $r_1 \geq d_3/[(2-\gamma)\theta^*_{2f}]$. At the equilibrium proportion θ^*_{2f}, by definition, Zone 2 drivers are indifferent between staying and moving. It follows from (Equation A.7) and (Equation A.8) that θ^*_{2f} solves $r_2 = d_3/[(2-\gamma)\theta^*_{2f}]$. This gives $\theta^*_{2f} = d_3/[r_2(2-\gamma)]$. $\theta^*_{2f} = 1$ if $r_2 \leq d_3/(2-\gamma)$ and otherwise, θ^*_{2f} is found by equating (Equation A.7) and (Equation A.8), leading to $\theta^*_{2f} = d_3/[r_2(2-\gamma)]$, which is in the range $(0, 1)$ by $d_3 \in (0, 1]$, $r_2 \in (0, 1)$, and $\gamma \in [0, 1]$.

When $r_2 > d_3/(2-\gamma)$, since $\theta^*_{2f} = d_3/[r_2(2-\gamma)] \in (0, 1)$, the condition $r_1 \geq d_3/[(2-\gamma)\theta^*_{2f}]$ is equivalent to $r_1 > r_2$, which is satisfied by assumption. When $r_2 \leq d_3/(2-\gamma)$, since $\theta^*_{2f} = 1$, the condition $r_1 \geq d_3/[(2-\gamma)\theta^*_{2f}]$ is equivalent to $r_1 \geq d_3/(2-\gamma)$. Consequently, a unique solution θ^*_{2f} exists, and is equal to $\min\{1, d_3/[r_2(2-\gamma)]\}$ in the region $r_1 \geq d_3/(2-\gamma)$.

(b) All Zone 1 drivers move in equilibrium if and only if, given θ^*_{2f}, i.e., the equilibrium proportion of Zone 2 drivers that move, their expected earnings from moving are greater than or equal to those from staying for $\theta^*_{1f} = 1$. It follows from (Equation A.5) and (Equation A.6) that all Zone 1 drivers move if and only if $r_1 \leq d_3/[(1+\gamma) + (2-\gamma)\theta^*_{2f}]$.

Moreover, all Zone 2 drivers move given $\theta^*_{1f} = 1$ if and only if the expected earnings from moving are greater than or equal to those from staying for $\theta^*_{2f} = 1$. Thus, all Zone 2 drivers move given $\theta^*_{1f} = 1$ if and only if $r_2 < d_3/[2-\gamma+1+\gamma] = d_3/3$. Plugging $\theta^*_{2f} = 1$ into the threshold for r_1 yields $r_1 \leq d_3/3$. Since $r_1 > r_2$, $r_1 \leq d_3/3$ is sufficient for $\theta^*_{1f} = \theta^*_{2f} = 1$

(c) All Zone 2 drivers move in equilibrium if and only if, given θ^*_{1f}, i.e., the equilibrium proportion of Zone 1 drivers that move, their expected earnings from moving are greater than or equal to those from staying for $\theta^*_{2f} = 1$. It follows from (Equation A.7) and (Equation A.8) that all Zone 2 drivers move if and only if $r_2 \leq d_3/[(1+\gamma)\theta^*_{1f} + (2-\gamma)]$. At the equilibrium proportion θ^*_{1f}, by definition, Zone 1 drivers are indifferent between staying and moving. It follows from (Equation A.5) and (Equation A.6) that θ^*_{1f} is obtained by solving $r_1 = d_3/[(1+\gamma)\theta^*_{1f} + (2-\gamma)]$, which yields $\theta^*_{1f} = [d_3 - r_1(2-\gamma)]/[r_1(1+\gamma)]$.

Then, since the denominator in $[d_3 - r_1(2-\gamma)]/[r_1(1+\gamma)]$ is strictly positive by $r_1 \in (0,1)$ and $\gamma \in [0,1]$, we have $\theta^*_{1f} \in (0,1)$ if and only if $r_1 < d_3/(2-\gamma)$ and $d_3 - r_1(2-\gamma) < r_1(1+\gamma)$. Note that $d_3 - r_1(2-\gamma) < r_1(1+\gamma)$ is equivalent to $r_1 > d_3/3$, and therefore, the two conditions on r_1 are opposite to those in Propositions 6a and 6b, respectively. Furthermore, plugging θ^*_{1f} into the condition on r_2 yields $r_2 < r_1$, which is satisfied by assumption.

Proposition 7. *When $r_1 = r_2 = 0$, with surge information sharing but not with full information sharing, demand in all three zones is fully met in equilibrium.*

Proof of Proposition 7 For brevity, we continue to express the proportions $\theta_{1s}(d_3)$, $\theta_{2s}(d_3)$, $\theta_{1f}(d_1, d_2, d_3)$, and $\theta_{2f}(d_1, d_2, d_3)$, as θ_{1s}, θ_{2s}, θ_{1f}, and θ_{2f}, respectively.

We will consider three types of equilibria under surge information sharing, under $r_1 = r_2 = 0$ and $d_3 > 0$: Where only Zone 2 drivers move, where only Zone 1 drivers move, and where some proportion of drivers move from Zones 1 and 2. Finally, we will consider the unique equilibrium under $r_1 = r_2 = 0$ and $d_3 = 0$ where no drivers from Zones 1 or 2 move. We will show that the supply levels in Zones 1 and 2 under each equilibrium are such that $(1+\gamma)(1-\theta_{1s}^*) \geq 1$ and $(2-\gamma)(1-\theta_{2s}^*) \geq 1$, respectively, which would imply that $d_1 \in [0,1]$ and $d_2 \in [0,1]$ are always met. We will also show that the equilibrium supply in Zone 3 is such that $(1+\gamma)\theta_{1s}^* + (2-\gamma)\theta_{2s}^* \geq d_3$ for all $d_3 \in [0,1]$.

We first consider the equilibrium in which $\theta_{1s}^* = 0$ and $\theta_{2s}^* \in (0,1)$. Here, $\theta_{1s}^* = 0$ is guaranteed by the condition that Zone 1 drivers' expected earnings from staying exceed those from moving given θ_{2s}^*, which is equivalent to $\frac{1}{(1+\gamma)} \geq \frac{d_3}{(2-\gamma)\theta_{2s}^*}$. By definition, at equilibrium θ_{2s}^*, Zone 2 drivers are indifferent between staying and moving given $\theta_{1s}^* = 0$. Then, it follows that θ_{2s}^* obtained by solving $\frac{1}{(2-\gamma)(1-\theta_{2s}^*)} = \frac{d_3}{(2-\gamma)\theta_{2s}^*}$ equals $\frac{d_3}{1+d_3}$. Firstly, in Zone 1, $(1+\gamma)(1-\theta_{1s}^*) = (1+\gamma) \geq 1$, by $\gamma \in [0,1]$, which implies that the supply in Zone 1 exceeds demand $d_1 \in [0,1]$. Secondly, in Zone 3, $(1+\gamma)\theta_{1s}^* + (2-\gamma)\theta_{2s}^* = (2-\gamma)\theta_{2s}^* \geq d_3(1+\gamma) \geq d_3$, in which the first inequality holds due to the condition that guarantees Zone 1 drivers would not move, $\frac{1}{(1+\gamma)} \geq \frac{d_3}{(2-\gamma)\theta_{2s}^*}$, and the second inequality holds by $\gamma \geq 0$. Lastly, in Zone 2, $(2-\gamma)(1-\theta_{2s}^*) \geq 1$, because θ_{2s}^* solves $\frac{1}{(2-\gamma)(1-\theta_{2s}^*)} = \frac{d_3}{(2-\gamma)\theta_{2s}^*}$, and the right-hand side is less than or equal to 1 because it follows from the analysis for Zone 3 that $(2-\gamma)\theta_{2s}^* \geq d_3$. Therefore, the supply in Zone 2, $(2-\gamma)(1-\theta_{2s}^*)$, exceeds demand $d_2 \in [0,1]$, and demand in all zones is fully met in equilibrium.

Next, we consider the equilibrium in which $\theta_{2s}^* = 0$ and $\theta_{1s}^* \in (0,1)$. Here, $\theta_{2s}^* = 0$ is guaranteed by the condition that Zone 2 drivers' expected earnings from staying exceed those from moving given θ_{1s}^*, which is equivalent to $\frac{1}{(2-\gamma)} \geq \frac{d_3}{(1+\gamma)\theta_{1s}^*}$. By definition, at equilibrium θ_{1s}^*, Zone 1 drivers are indifferent between staying and moving given $\theta_{2s}^* = 0$. Then, it follows that θ_{1s}^* obtained by solving $\frac{1}{(1+\gamma)(1-\theta_{1s}^*)} = \frac{d_3}{(1+\gamma)\theta_{1s}^*}$ equals $\frac{d_3}{1+d_3}$. Firstly, in Zone 2, $(2-\gamma)(1-\theta_{2s}^*) = (2-\gamma) \geq 1$ by $\gamma \in [0,1]$, which implies that the supply in Zone 2 exceeds demand $d_2 \in [0,1]$. Secondly, in Zone 3, $(1+\gamma)\theta_{1s}^* + (2-\gamma)\theta_{2s}^* = (1+\gamma)\theta_{1s}^* \geq d_3(2-\gamma) \geq d_3$, in which the first inequality holds due to the condition that guarantees that Zone 2 drivers would not move, $\frac{1}{(2-\gamma)} \geq \frac{d_3}{(1+\gamma)\theta_{1s}^*}$, and the second inequality holds by $\gamma \in [0,1]$. Lastly, in Zone 1, $(1+\gamma)(1-\theta_{1s}^*) \geq 1$, because θ_{1s}^* solves $\frac{1}{(1+\gamma)(1-\theta_{1s}^*)} = \frac{d_3}{(1+\gamma)\theta_{1s}^*}$, where the right-hand side is less than or equal to 1 because it follows from the analysis for Zone 3 that $(1+\gamma)\theta_{1s}^* \geq d_3$. Therefore, the supply in Zone 1, $(1+\gamma)(1-\theta_{1s}^*)$ exceeds demand $d_1 \in [0,1]$, and demand in all zones is fully met in equilibrium.

Next, we evaluate the equilibrium in which, by definition, drivers in Zones 1 and 2 are indifferent between staying and moving at θ_{1s}^* and θ_{2s}^*. It follows from (Equation A.1) and (Equation A.2), and (Equation A.3) and (Equation A.4), that θ_{1s}^* and θ_{2s}^* are given by

$$\theta_{1s}^* = \frac{-1+2\gamma+d_3(1+\gamma)}{(2+d_3)(1+\gamma)},$$

$$\theta_{2s}^* = \frac{1-2\gamma+d_3(2-\gamma)}{(2+d_3)(1+\gamma)}.$$

The equilibrium supply in Zone 3, $(1+\gamma)\theta_{1s}^* + (2-\gamma)\theta_{2s}^* = \frac{3d_3}{2+d_3} \geq d_3$, because $2+d_3 \leq 3$ by $d_3 \in (0,1]$. Moreover, the equilibrium supply levels in Zones 1 and 2 are such that $(1+\gamma)(1-\theta_{1s}^*) \geq 1$ and $(2-\gamma)(1-\theta_{2s}^*) \geq 1$ because θ_{1s}^* and θ_{2s}^* solve $\frac{1}{(1+\gamma)(1-\theta_{1s}^*)} = \frac{d_3}{(1+\gamma)\theta_{1s}^*+(2-\gamma)\theta_{2s}^*}$ and $\frac{1}{(2-\gamma)(1-\theta_{2s}^*)} = \frac{d_3}{(1+\gamma)\theta_{1s}^*+(2-\gamma)\theta_{2s}^*}$, respectively, where the right-hand side of both equations is less than or equal to 1 by $(1+\gamma)\theta_{1s}^* + (2-\gamma)\theta_{2s}^* \geq d_3$. Therefore, the supply in Zones 1 and 2, $(1+\gamma)(1-\theta_{1s}^*)$ and $(2-\gamma)(1-\theta_{2s}^*)$, exceeds $d_1 \in [0,1]$ and $d_2 \in [0,1]$, respectively, and demand in all zones is fully met in equilibrium.

Finally, if $d_3 = 0$, the unique equilibrium is $\theta_{1s}^* = \theta_{2s}^* = 0$. The demand in Zones 1 and 2 is covered in equilibrium because $(1+\gamma)(1-\theta_{1s}^*) = (1+\gamma) \geq 1$ and $(2-\gamma)(1-\theta_{2s}^*) = (2-\gamma) \geq 1$. Therefore, demand is fully met in equilibrium.

Next, we will consider three types of equilibria under full information sharing, under $r_1 = r_2 = 0$ and $d_3 > 0$: Where only Zone 2 drivers move, where only Zone 1 drivers move, and where some proportion of drivers move from Zones 1 and 2. We will compare the equilibrium supply in Zone 1, $(1+\gamma)(1-\theta_{1f}^*)$, against d_1, the equilibrium supply in Zone 2, $(2-\gamma)(1-\theta_{2f}^*)$ against d_2, and that in Zone 3, $(1+\gamma)\theta_{1f}^* + (2-\gamma)\theta_{2f}^*$, against d_3.

We first consider the equilibrium in which $\theta_{1f}^* = 0$ and $\theta_{2f}^* \in (0,1]$. Here, $\theta_{1f}^* = 0$ is guaranteed by the condition that Zone 1 drivers' expected earnings from staying exceed those from moving given θ_{2f}^*, which is equivalent to $\frac{2d_1}{(1+\gamma)} \geq \frac{d_3}{(2-\gamma)\theta_{2f}^*}$. By definition, at equilibrium θ_{2f}^*, Zone 2 drivers are indifferent between staying and moving given $\theta^*_{1f} = 0$. Then, it follows that θ^*_{2f} obtained by solving $\frac{2d_2}{(2-\gamma)(1-\theta^*_{2f})} = \frac{d_3}{(2-\gamma)\theta^*_{2f}}$ equals $\frac{d_3}{2d_2+d_3}$. Plugging θ^*_{2f} into the condition that guarantees $\theta^*_{1f} = 0$, we obtain $\frac{2d_1}{1+\gamma} \geq \frac{2d_2+d_3}{2-\gamma}$. Firstly, in Zone 1, the supply level satisfies $(1+\gamma)(1-\theta^*_{1f}) = (1+\gamma) \geq d_1$ by $\gamma \in [0,1]$ and $d_1 \in [0,1]$. Secondly, in Zone 3, the supply level satisfies $(1+\gamma)\theta^*_{1f} + (2-\gamma)\theta^*_{2f} = \frac{(2-\gamma)d_3}{2d_2+d_3} \geq d_3$ if and only if $2d_2 + d_3 \leq (2-\gamma)$. Lastly, in Zone 2, the supply level satisfies $(2-\gamma)(1-\theta^*_{2f}) \geq d_2$ if and only if $2d_2 + d_3 \leq 2(2-\gamma)$. In the parameter region where $\frac{2d_1}{1+\gamma} \geq \frac{2d_2+d_3}{2-\gamma}$ and $2d_2 + d_3 > (2-\gamma)$, demand in Zone 3 is not met in equilibrium. We can verify that this region is non-empty; one such parameter instance is $\{d_1 = 1, d_2 = 3/4, d_3 = 1/2, \gamma = 1/2\}$.

Next, we consider the equilibrium in which $\theta^*_{2f} = 0$ and $\theta^*_{1f} \in (0,1]$. Here, $\theta^*_{2f} = 0$ is guaranteed by the condition that Zone 2 drivers' expected earnings from staying exceed those from moving given θ^*_{1f}, which is equivalent to $\frac{2d_2}{(2-\gamma)} \geq \frac{d_3}{(1+\gamma)\theta^*_{1f}}$. By definition, at equilibrium θ^*_{1f}, Zone 1 drivers are indifferent between staying and moving given $\theta^*_{2f} = 0$. Then, it follows that θ^*_{1f} obtained by solving $\frac{2d_1}{(1+\gamma)(1-\theta^*_{1f})} = \frac{d_3}{(1+\gamma)\theta^*_{1f}}$ equals $\frac{d_3}{2d_1+d_3}$. Plugging θ^*_{1f} into the condition that guarantees $\theta^*_{2f} = 0$, we obtain $\frac{2d_2}{2-\gamma} \geq \frac{2d_1+d_3}{1+\gamma}$. Firstly, in Zone 2, the supply level satisfies $(2-\gamma)(1-\theta^*_{2f}) = (2-\gamma) \geq d_2$ by $\gamma \in [0,1]$ and $d_2 \in [0,1]$. Secondly, in Zone 3, $(1+\gamma)\theta^*_{1f} + (2-\gamma)\theta^*_{2f} = \frac{(1+\gamma)d_3}{2d_1+d_3} \geq d_3$ if and only if $2d_1+d_3 \leq (1+\gamma)$. Lastly, in Zone 1, $(1+\gamma)(1-\theta^*_{1f}) \geq d_1$ if and only if $2d_1+d_3 \leq 2(1+\gamma)$. In the parameter region where $\frac{2d_2}{2-\gamma} \geq \frac{2d_1+d_3}{1+\gamma}$ and $2d_1+d_3 > (1+\gamma)$, demand in Zone 3 is not fully met in equilibrium. We can verify that this region is non-empty; one such parameter instance is $\{d_1 = 5/8, d_2 = 1, d_3 = 1/2, \gamma = 1/2\}$.

Next, we evaluate the equilibrium in which, by definition, drivers in Zones 1 and 2 are indifferent between staying and moving at θ^*_{1f} and θ^*_{2f}. It follows from (Equation A.5) and (Equation A.6), and (Equation A.7) and (Equation A.8), that θ^*_{1f} and θ^*_{2f} are given by

$$\theta^*_{1f} = \frac{-4d_1 + 2d_2 + d_3 + 2d_1\gamma + 2d_2\gamma + d_3\gamma}{(2d_1 + 2d_2 + d_3)(1+\gamma)},$$

$$\theta^*_{2f} = \frac{4d_1 - 2d_2 + 2d_3 - 2d_1\gamma - 2d_2\gamma - d_3\gamma}{(2d_1 + 2d_2 + d_3)(2-\gamma)}.$$

Here, $\theta_{1f}^* < 1$ and $\theta_{2f}^* < 1$ are equivalent to $-4d_1(1+\gamma) < 0$ and $-4d_2(2-\gamma) < 0$, respectively, which hold for $\{d_1, d_2\} > 0$ by $\gamma \in [0,1]$. $\theta_{1f}^* > 0$ is equivalent to $\frac{2d_1}{1+\gamma} < \frac{2d_2+d_3}{2-\gamma}$ and $\theta_{2f}^* > 0$ is equivalent to $\frac{2d_2}{2-\gamma} < \frac{2d_1+d_3}{1+\gamma}$. These conditions are opposite to those given above that guarantee $\theta_{1f}^* = 0$ and $\theta_{2f}^* \in (0,1]$ and $\theta_{1f}^* \in (0,1]$ and $\theta_{2f}^* = 0$, respectively.

Firstly, in Zones 1 and 2, the supply levels satisfy $(1+\gamma)(1-\theta_{1f}^*) = \frac{6d_1}{2(d_1+d_2)+d_3} > d_1$ and $(2-\gamma)(1-\theta_{2f}^*) = \frac{6d_2}{2(d_1+d_2)+d_3} > d_2$, respectively, because $2(d_1+d_2)+d_3 < 6$ by $\{d_1, d_2\} \in [0,1]$ and $d_3 \in (0,1]$. Finally, the equilibrium supply in Zone 3 is given by $(1+\gamma)\theta_{1f}^* + (2-\gamma)\theta_{2f}^* = \frac{3d_3}{2(d_1+d_2)+d_3}$, which is greater than or equal to d_3 if and only if $2(d_1+d_2)+d_3 \le 3$. In the parameter region where $\frac{2d_1}{1+\gamma} < \frac{2d_2+d_3}{2-\gamma}$, $\frac{2d_2}{2-\gamma} < \frac{2d_1+d_3}{1+\gamma}$, and $2(d_1+d_2)+d_3 > 3$, demand in Zone 3 is not fully met in equilibrium. We can verify that this region is non-empty; one such parameter instance is $\{d_1 = d_2 = d_3 = 1, \gamma \in (0.2, 0.8)\}$.

A.2 Supplemental Figures, Tables, and Analysis

A.2.1 Comparison of Expected Matching Efficiency considering both Stages

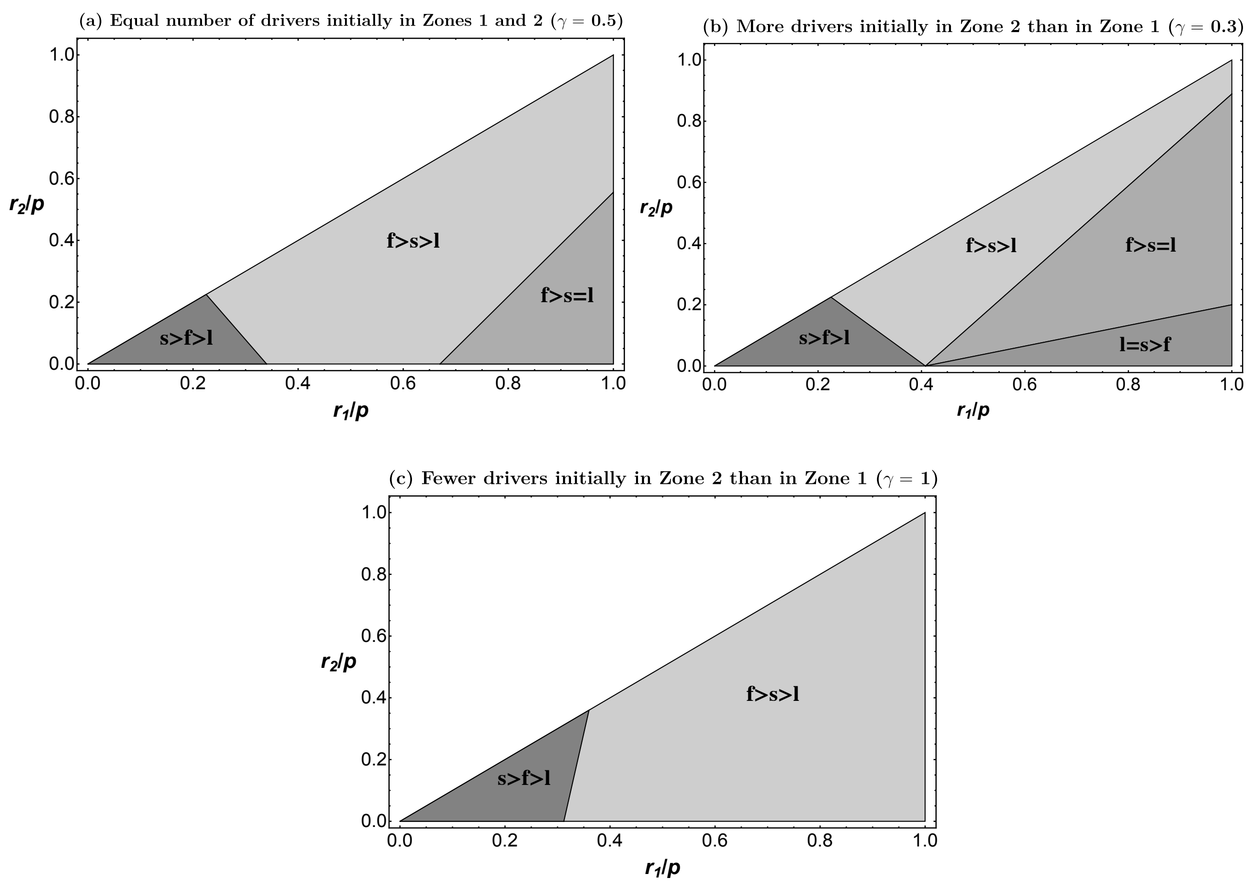


Figure A.1: Comparison of expected matching efficiency across two stages under full, surge, and local information mechanisms.

A.2.2 Comparison of Experimental and Theoretically Predicted Matching Efficiency

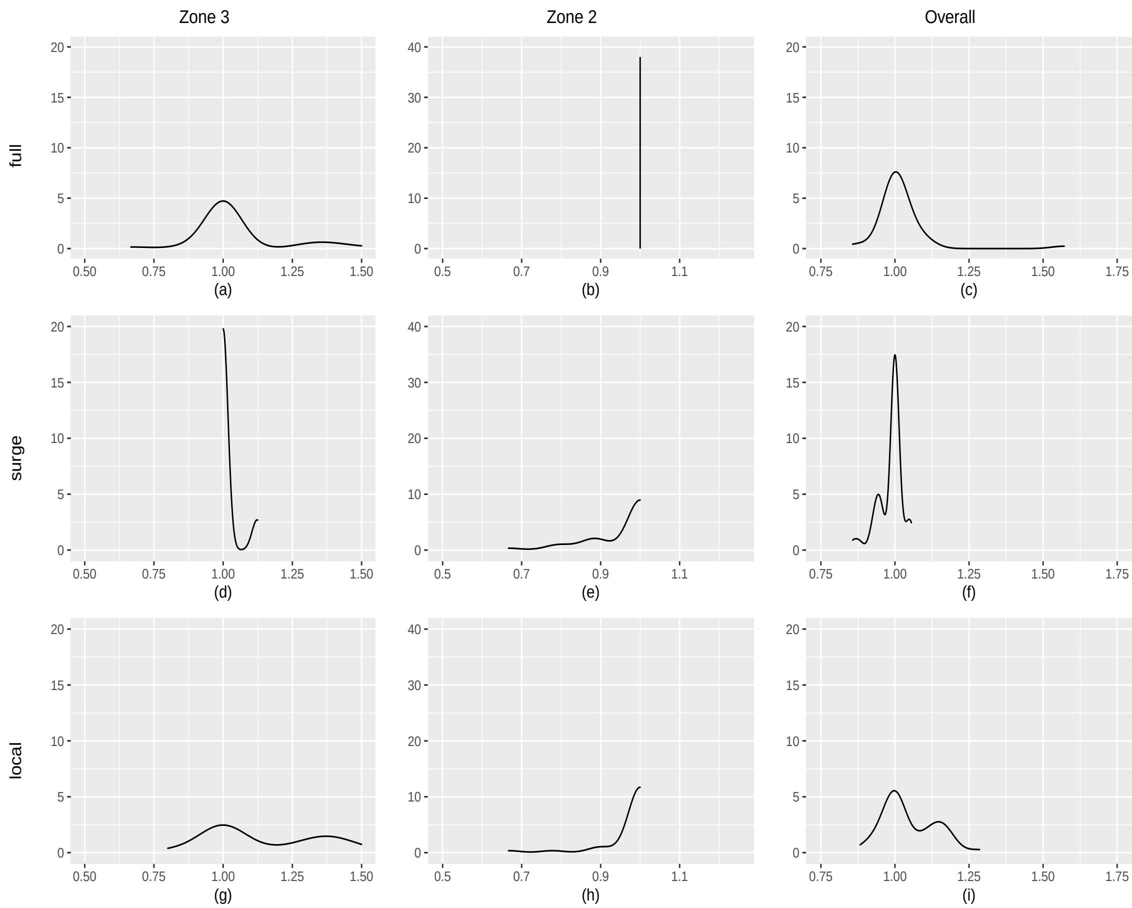


Figure A.2: Density plots for (experimental matching efficiency/theoretically predicted matching efficiency) in Zone 3 (the surge zone), Zone 2, and for all zones.

A.2.3 Linear Hypotheses for Analysis of Effects in Regression Models

Table A.1: Experimental vs. theoretically-predicted matching efficiency: Linear hypothesis tests

Treatment	Linear Hypothesis (Null)
full	$\lambda_0 + 20\lambda_3 = 0$
surge	$\lambda_0 + \lambda_1 + 20(\lambda_3 + \lambda_4) = 0$
local	$\lambda_0 + \lambda_2 + 20(\lambda_3 + \lambda_5) = 0$

Table A.2: Matching efficiency comparisons across treatments: Linear hypothesis tests

Treatment	Linear Hypothesis (Null)
full vs. *surge*	$\beta_1 + 20\beta_4 \geq 0$
full vs. *local*	$\beta_2 + 20\beta_5 \leq 0$
surge vs. *local*	$(\beta_1 + 20\beta_4) - (\beta_2 + 20\beta_5) \geq 0$

Table A.3: Observed vs. predicted frequency of movement: Linear hypothesis tests

Treatment	Linear Hypothesis (Null)
full	$\alpha_0 + 20\alpha_3 = 0$
surge	$\alpha_0 + \alpha_1 + 20(\alpha_3 + \alpha_4) = 0$
local	$\alpha_0 + \alpha_2 + 20(\alpha_3 + \alpha_5) = 0$

A.2.4 Driver Payoffs and Utilization

Here, we examine the drivers' outcomes in our experiments. Specifically, we consider two performance metrics, drivers' payoffs and utilization in Stage 2. Driver payoff captures the utility arising from the driver's relocation decision in a period, i.e., the fare income generated by the driver over the two stages minus the cost of moving, and excludes any penalties related to the real-effort task. Utilization captures the percentage of time that a driver is matched with a rider in Stage 2. Experimental values and theory predictions for both metrics are reported in Table A.4. In this table, we treat the average payoff and utilization for each driver as an independent unit of observation and the standard deviation indicates the variation across drivers.

All treatments are comparable in terms of driver payoffs (two-sided p-values in Wilcoxon tests are 0.672, 0.949, and 0.715, for full vs. surge, full vs. local, and surge vs. local, respectively)

Table A.4: Driver-level metrics

Treatment	Driver Utilization (Stage 2)		Driver Payoffs	
	Theory	Experiment	Theory	Experiment
full	0.476	0.487 (0.110)	7.51	7.41 (2.32)
surge	0.483	0.474 (0.112)	7.67	7.43 (2.89)
local	0.452	0.470 (0.100)	7.70	7.44 (2.50)

Note: Standard deviations shown in parentheses are taken across participant-level averages.

and utilization (two-sided p-values are 0.519, 0.473, and 0.974, for full vs. surge, full vs. local, and surge vs. local, respectively). Furthermore, driver performance is comparable to the theory prediction for each treatment (two-sided p-values using Wilcoxon tests for full, surge and local, respectively, are 0.820, 0.475, and 0.576, for driver payoffs, and 0.960, 0.653, and 0.735, for utilization)[1]. *Overall, all information-sharing mechanisms perform equally well from the drivers' perspective in our experiments.*

A.2.5 Regression Model for Drivers' Decisions with Lagged Variables

In Table A.5, we include lagged variables in our analysis of the drivers' decisions over time to capture the effect of previous decisions and outcomes. In this analysis, Lag_Choice variable captures the driver's previous decision ($= 1$ if the driver moved previously, and 0 otherwise), while $Lag\_Earnings$ captures the driver's earnings from the previous round plus the corresponding relocation cost for the driver's initial zone. This variable is presented in a normalized manner to facilitate the interpretation since $Lag\_Earnings$ equals 0 when a driver chose to move in the previous round but was not assigned a ride upon moving.

[1]We find consistent results when a regression model, which includes time and random effects for participants, and linear hypothesis testing approach similar to subsection 2.6.1 are utilized to examine differences across treatments and from theory. These results are excluded for brevity and available upon request.

Table A.5: Effect of information on drivers' decisions. Logistic regression models with random-effects for individuals and lagged variables.

	Dependent variable: $logit(Pr(c_{it}^{j} = 1))$					
	Zone 1 full	Zone 2 full	Zone 1 surge	Zone 2 surge	Zone 1 local	Zone 2 local
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-1.162^{**}	-2.277^{**}	-3.022^{**}	-1.479^{**}	$-0.681^{\dagger}$	-2.143^{**}
	(0.396)	(0.770)	(0.516)	(0.528)	(0.365)	(0.485)
d_1	-0.074^{**}	0.154^{**}				
	(0.024)	(0.053)				
d_2	0.074^{**}	-0.262^{**}				
	(0.025)	(0.060)				
d_3	0.151^{**}	0.239^{**}	0.395^{**}	0.100^{*}	$-0.057^{\dagger}$	0.230^{**}
	(0.032)	(0.076)	(0.043)	(0.050)	(0.032)	(0.061)
t	0.001	-0.055^{**}	$-0.016^{\dagger}$	-0.017	-0.004	-0.029^{*}
	(0.007)	(0.016)	(0.009)	(0.011)	(0.007)	(0.013)
Lag_Choice	-0.643^{*}	-0.093	-0.423	-0.589	0.067	$-1.120^{\dagger}$
	(0.270)	(0.632)	(0.330)	(0.439)	(0.268)	(0.668)
$Lag\_Earnings$	-0.029^{*}	-0.021	-0.045^{*}	-0.016	-0.015	-0.038^{**}
	(0.014)	(0.023)	(0.017)	(0.016)	(0.014)	(0.017)
$Lag\_Choice \times Lag\_Earnings$	$0.055^{\dagger}$	-0.129	0.128^{**}	0.170^{**}	0.095^{**}	0.158^{*}
	(0.030)	(0.098)	(0.037)	(0.054)	(0.029)	(0.073)
Observations	819	429	858	429	858	429

The variable Lag_Choice captures the choice of participant i from Zone j in period $(t-1)$ ($=1$ if the driver moved previously and 0 otherwise). The variable $Lag\_Earnings$ captures the earnings of participant i in period $(t-1)$ plus the corresponding relocation cost for the participant's initial zone. Standard errors in parentheses. †p<0.1; *p<0.05; **p<0.01.

In Table A.5, we observe that after controlling for drivers' decisions and their outcomes from the previous period, participants' relocation decisions continue to be significantly influenced by the demand information available to them. Additionally, results from Table A.5 support the notion that previous decisions and outcomes do have some influence on drivers' subsequent decisions: Holding everything else fixed, (i) a driver that previously chose to stay is more likely to continue to do so upon receiving higher earnings (as evident from the coefficient of $Lag\_Earnings$, which is negative for drivers across all treatments and zones, and is significant for Zone 1 drivers in the full and surge treatments, and Zone 2 drivers in the local treatment.). (ii) In contrast, a driver that previously chose to move may be less likely to do so in the next round upon not being assigned a ride (as evident from the coefficient of Lag_Choice, which is negative for drivers across all treatments and zones, and is significant for Zone 1 drivers in the full information treatment, and Zone 2 drivers in the local information treatment). (iii) However, achieving higher earnings upon moving increases the attractiveness of moving again in the next round (as evident from the positive and significant coefficients of $Lag\_Choice \times Lag\_Earnings$ for drivers in all treatments and zones except for Zone 2 drivers in the full treatment).

A.2.6 Effect of Participants' Prior Practical Experience on their Decisions

Here, we analyze whether the presence of prior practical experience of working as a service provider for a gig economy platform influences participants' decisions. To that end, we re-run the regression model in (Equation 2.17) with an additional control variable, EXP_i, which equals 1 if participant i stated in the post-experiment questionnaire that had he/she had practical experience of working as a service provider for a gig economy platform, and equals 0 otherwise. Results are reported in Table A.6. We observe that the coefficient on the binary variable EXP is insignificant, indicating consistent behavior among human participants with and without practical experience.

Table A.6: Observed vs. predicted probability of moving: Regression models with random-effects for individuals while controlling for participants' experience of working for a platform.

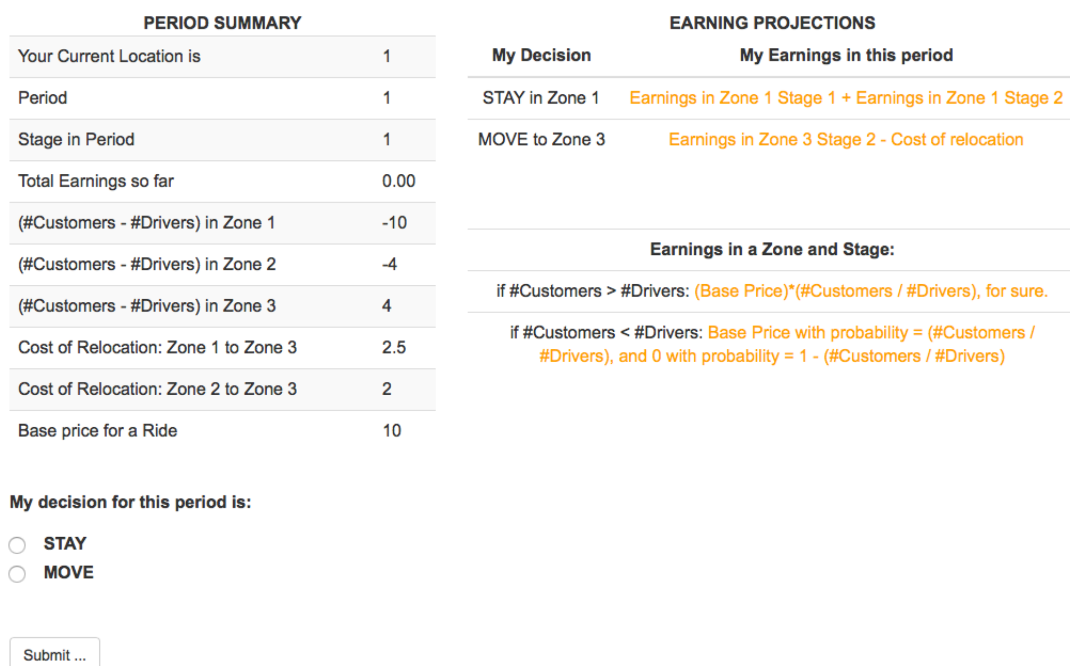
	Dependent variable: (c^j - θ^j)
	All Drivers pooled
	(1)
Constant	0.020
	(0.041)
TRS	0.118*
	(0.056)
TRL	0.115*
	(0.056)
t	0.0004
	(0.001)
$TRS \times t$	$-0.002^{\dagger}$
	(0.001)
$TRL \times t$	$-0.003^{\dagger}$
	(0.001)
EXP	0.096
	(0.063)
Observations	3920

The variable EXP equals 1 if the participant had prior experience of working for a platform as a driver, and equals 0 otherwise. Standard errors in parentheses. †p<0.1; *p<0.05; **p<0.01.

A.3 Additional Details of the Experimental Setup

Table A.7: Information structure for Stage 2

Mismatch Information	**Full Information**			**Surge Information**			**Local information**		
Available to Drivers in:	Zone 1	Zone 2	Zone 3	Zone 1	Zone 2	Zone 3	Zone 1	Zone 2	Zone 3
Zone 1	✓	✓	✓	✓(if $d_1 > s_{12}$)	✓(if $d_2 > s_{22}$)	✓(if $d_3 > s_{32}$)	✓(if $d_1 > s_{12}$)		
Zone 2	✓	✓	✓	✓(if $d_1 > s_{12}$)	✓(if $d_2 > s_{22}$)	✓(if $d_3 > s_{32}$)		✓(if $d_2 > s_{22}$)	✓(if $d_3 > s_{32}$)
Zone 3	✓	✓	✓	✓(if $d_1 > s_{12}$)	✓(if $d_2 > s_{22}$)	✓(if $d_3 > s_{32}$)		✓(if $d_2 > s_{22}$)	✓(if $d_3 > s_{32}$)



PERIOD SUMMARY

Your Current Location is	1
Period	1
Stage in Period	1
Total Earnings so far	0.00
(#Customers - #Drivers) in Zone 1	-10
(#Customers - #Drivers) in Zone 2	-4
(#Customers - #Drivers) in Zone 3	4
Cost of Relocation: Zone 1 to Zone 3	2.5
Cost of Relocation: Zone 2 to Zone 3	2
Base price for a Ride	10

EARNING PROJECTIONS

My Decision	**My Earnings in this period**
STAY in Zone 1	Earnings in Zone 1 Stage 1 + Earnings in Zone 1 Stage 2
MOVE to Zone 3	Earnings in Zone 3 Stage 2 - Cost of relocation

Earnings in a Zone and Stage:

if #Customers > #Drivers: (Base Price)*(#Customers / #Drivers), for sure.

if #Customers < #Drivers: Base Price with probability = (#Customers / #Drivers), and 0 with probability = 1 - (#Customers / #Drivers)

My decision for this period is:

STAY

MOVE

Submit ...

Figure A.3: Screen 1 (full treatment): Decision area

STAGE 1

	ZONE 1	ZONE 2	ZONE 3	Ride Assigned/Not	(Earnings - Relocation Cost)
INITIAL (#Customers - #Drivers) Stage 1	-10	-4	4		
FINAL (#Customers - #Drivers) Stage 1	-3(✓)	0	4	NO	0.00

(✓) Marks Your Presence in the Zone During Allocation of Customer Demand

If You Decided to Move, None of the Zones Will Have the (✓) Mark

Sign Number: 1

Please select the appropriate action for the traffic sign displayed above.

GO | STOP | Curve Left | Curve Right | Slow Down | Turn Left | Turn Right

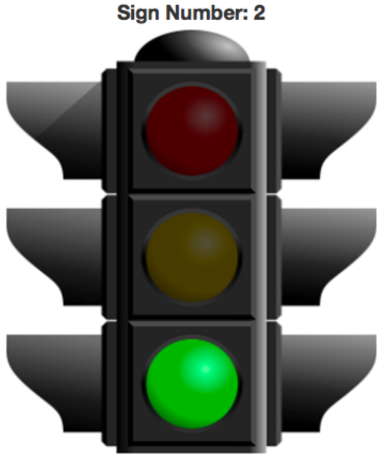
Figure A.4: Screen 2 (full treatment): Stage 1

STAGE 2

	ZONE 1	ZONE 2	ZONE 3	Ride Assigned/Not	Earnings
(#Customers - #Drivers) Stage 2	-3	0	-7(✓)	YES	10.00

(✓) Marks Your Presence in the Zone During Allocation of Customer Demand

Sign Number: 2



Please select the appropriate action for the traffic sign displayed above.

GO STOP Curve Left Curve Right Slow Down Turn Left Turn Right

Figure A.5: Screen 3 (full treatment): Stage 2

Results

Period	STAGE 1: INITIAL (#Customers - #Drivers) [Zone 1, Zone 2, Zone 3]	My Decision	STAGE 1: FINAL (#Customers - #Drivers) [Zone 1, Zone 2, Zone 3]	STAGE 2: (#Customers - #Drivers) [Zone 1, Zone 2, Zone 3]	Ride Assigned (Stage 1)	Ride Assigned (Stage 2)	My Earnings (Stage 1)	My Earnings (Stage 2)	Deducted Credits (Stage 1 & 2)	Relocation Cost	My Earnings in Period	Cumulative Earnings
1	-10, -4, 4	MOVE	-3, 0, 4	-3, 0, -7	0	1	0.00	10.00	0.2, 0.2	2.5	7.10	7.10

Continue ...

Figure A.6: Screen 4 (full treatment): Period result

APPENDIX B
SUPPLEMENTAL MATERIALS FOR CHAPTER 3

B.1 Experimental Materials

B.1.1 Post-experiment Questionnaire

1. Please answer the following (Strongly disagree (1)-Strongly agree (7))
   (a) I would trust the Platform
   (b) I would rely on the Platform
   (c) The Platform is honest
   (d) The Platform is safe
   (e) The Platform sincerely cares about the welfare of workers
   (f) The Platform sincerely cares about providing workers with sufficient information
   (g) The Platform treats workers fairly
   (h) I believe that the information provided by the Platform is correct
2. The Platform is:
   (a) Extremely unfavorable (1)-Extremely favorable (7)
   (b) Extremely negative (1)-Extremely positive (7)
   (c) Extremely bad (1)-Extremely good (7)
   (d) Extremely not likable (1)-Extremely likable (7)
3. The Platform is:
   (a) The Platform is: Extremely attractive to work for (1)–Extremely unattractive to work for (7)

Note: The four items on trust (1a–1d) are based on Chaudhuri and Holbrook (2001). The item on accuracy of information (1h) and the items on favorability (2a–2d) are based on Yoon et al. (2006). The items on sincerity (1e–1f) and attractiveness to work for (3a) are adapted from Buell and Kalkanci (2021).

Questions about algorithm change (shown only to those who see algorithm change):

In reference to the change in payment algorithm implemented by the Platform, to what extent do you disagree or agree with the following statements?

1. The Platform's implementation of change in payment algorithm was fair (Strongly disagree (1)-Strongly agree (7))

2. Compared to the payment algorithm used by the Platform for the first task, the algorithm used after the change was appropriate (Absolutely inappropriate (1)- Absolutely appropriate (7))

3. Earnings from the payment algorithm used by the Platform for the first task often exceed those from the payment algorithm used after the change (Strongly disagree (1)-Strongly agree (7))

Table B.1: Cronbach's α for variables created from post-experiment questionnaire item-responses

Variable	Study 1	Study 2	Study 3
$Trust_i$	0.938	0.956	0.931
$Sincerity_i$	0.822	0.879	0.812
$Favorability_i$	0.968	0.971	0.970

B.1.2 Risk Preference Elicitation

To elicit participants' risk preferences, they were presented with 10 pairs of lotteries, and for each pair, they were asked to choose the lottery (A or B) they would prefer to play. In lottery A (B), the possible outcomes were \$0.5 and \$0.4 (\$0.96 and \$0.09). The expected values of both lotteries increased going down the list. Lottery A (B) had a higher expected value in pairs 1–4 (5–10), and therefore, risk-neutral individuals maximizing their expected payoff were predicted to choose A for pairs 1–4 and B for pairs 5–10. A participant is considered risk averse if the participant switches from A to B at pair 6 or later, and is not considered to be risk averse otherwise. To incentivize subjects' choices, we informed them that one pair of lotteries would be randomly selected from the list and their choice would be played out. Participants earned a small bonus based on the outcome of the risk preference elicitation task over their earnings from the experiment.

B.1.3 Screens from Experimental Interface

Order Screen

Possible Order Compositions

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	30	w_1
Type 2	1 to 50	-	5	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	5	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	w_4
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	w_1
Type 2	1 to 50	-	30	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	5	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	w_4
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	w_1
Type 2	1 to 50	-	5	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	30	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	w_4
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	w_1
Type 2	1 to 50	-	5	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	5	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	30	w_4
Total			45	

Payment Algorithm: *[w_1 x (#items of Type 1)] + [w_2 x (#items of Type 2)] +*

[w_3 x (#items of Type 3)] + [w_4 x (#items of Type 4)]

Depending on the Order Composition you end up observing, and using the **Payment Algorithm** shown above, our payment to you for this order will be in the range:
$1.50 to $2.95 (*This excludes your Participation Cost*)

Participation Cost will be randomly drawn between $0 and $1.50 - each value being equally likely to be drawn. The order will be assigned to you if the amount you enter below is greater than or equal to the Participation Cost.

Using your Endowment of $1.50, what is the maximum amount you are willing to pay to participate and fulfill the order on the Platform? (You can use up to two decimal places, e.g., A.BC)

Figure B.1: WTP elicitation screen for non-intuitive + opaque treatment

Order Screen

Possible Order Compositions

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	30	$w_1 = 8.12$¢
Type 2	1 to 50	-	5	$w_2 = 4.98$¢
Type 3	1 to 5	16 to 64 oz (integer scale)	5	$w_3 = 3.02$¢
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	$w_4 = 2.31$¢
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	$w_1 = 8.12$¢
Type 2	1 to 50	-	30	$w_2 = 4.98$¢
Type 3	1 to 5	16 to 64 oz (integer scale)	5	$w_3 = 3.02$¢
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	$w_4 = 2.31$¢
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	$w_1 = 8.12$¢
Type 2	1 to 50	-	5	$w_2 = 4.98$¢
Type 3	1 to 5	16 to 64 oz (integer scale)	30	$w_3 = 3.02$¢
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	$w_4 = 2.31$¢
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	$w_1 = 8.12$¢
Type 2	1 to 50	-	5	$w_2 = 4.98$¢
Type 3	1 to 5	16 to 64 oz (integer scale)	5	$w_3 = 3.02$¢
Type 4	1 to 50	0 to 5 lb (decimal scale)	30	$w_4 = 2.31$¢
Total			45	

Payment Algorithm: *[w_1 x (#items of Type 1)] + [w_2 x (#items of Type 2)] + [w_3 x (#items of Type 3)] + [w_4 x (#items of Type 4)]*

Depending on the Order Composition you end up observing, and using the **Payment Algorithm** shown above, our payment to you for this order will be in the range:
$1.50 to $2.95 (*This excludes your Participation Cost*)

Participation Cost will be randomly drawn between $0 and $1.50 - each value being equally likely to be drawn. The order will be assigned to you if the amount you enter below is greater than or equal to the Participation Cost.

Using your Endowment of $1.50, what is the maximum amount you are willing to pay to participate and fulfill the order on the Platform? (You can use up to two decimal places, e.g., A.BC)

Figure B.2: WTP elicitation screen for non-intuitive + transparent treatment

Order Screen

Possible Order Compositions

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	30	w_1
Type 2	1 to 50	-	5	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	5	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	w_4
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	w_1
Type 2	1 to 50	-	30	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	5	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	w_4
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	w_1
Type 2	1 to 50	-	5	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	30	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	w_4
Total			45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	w_1
Type 2	1 to 50	-	5	w_2
Type 3	1 to 5	16 to 64 oz (integer scale)	5	w_3
Type 4	1 to 50	0 to 5 lb (decimal scale)	30	w_4
Total			45	

Payment Algorithm: *[w_1 x (#items of Type 1)] + [w_2 x (#items of Type 2)] + [w_3 x (#items of Type 3)] + [w_4 x (#items of Type 4)]*

Depending on the Order Composition you end up observing, and using the **Payment Algorithm** shown above, our payment to you for this order will be in the range (Our algorithm uses per-item payments (w_1, w_2, w_3, and w_4) that are based on the estimated time it takes to fulfill each item-type):
\$1.50 to \$2.95 (*This excludes your Participation Cost*)

Participation Cost will be randomly drawn between \$0 and \$1.50 - each value being equally likely to be drawn. The order will be assigned to you if the amount you enter below is greater than or equal to the Participation Cost.

Using your Endowment of \$1.50, what is the maximum amount you are willing to pay to participate and fulfill the order on the Platform? (You can use up to two decimal places, e.g., A.BC)

Figure B.3: WTP elicitation screen for intuitive + opaque treatment

Order Screen

Possible Order Compositions

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	30	$w_1 = 2.31¢$
Type 2	1 to 50	-	5	$w_2 = 3.02¢$
Type 3	1 to 5	16 to 64 oz (integer scale)	5	$w_3 = 4.98¢$
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	$w_4 = 8.12¢$
	Total		45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	$w_1 = 2.31¢$
Type 2	1 to 50	-	30	$w_2 = 3.02¢$
Type 3	1 to 5	16 to 64 oz (integer scale)	5	$w_3 = 4.98¢$
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	$w_4 = 8.12¢$
	Total		45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	$w_1 = 2.31¢$
Type 2	1 to 50	-	5	$w_2 = 3.02¢$
Type 3	1 to 5	16 to 64 oz (integer scale)	30	$w_3 = 4.98¢$
Type 4	1 to 50	0 to 5 lb (decimal scale)	5	$w_4 = 8.12¢$
	Total		45	

Item Type	Possible Item Positions	Possible Physical Weights	# Items	Per-Item Payments
Type 1	1 to 5	-	5	$w_1 = 2.31¢$
Type 2	1 to 50	-	5	$w_2 = 3.02¢$
Type 3	1 to 5	16 to 64 oz (integer scale)	5	$w_3 = 4.98¢$
Type 4	1 to 50	0 to 5 lb (decimal scale)	30	$w_4 = 8.12¢$
	Total		45	

Payment Algorithm: *[w_1 x (#items of Type 1)] + [w_2 x (#items of Type 2)] + [w_3 x (#items of Type 3)] + [w_4 x (#items of Type 4)]*

Depending on the Order Composition you end up observing, and using the **Payment Algorithm** shown above, our payment to you for this order will be in the range (Our algorithm uses per-item payments (w_1 , w_2 , w_3 , and w_4) that are based on the estimated time it takes to fulfill each item-type):
\$1.50 to \$2.95 (*This excludes your Participation Cost*)

Participation Cost will be randomly drawn between \$0 and \$1.50 - each value being equally likely to be drawn. The order will be assigned to you if the amount you enter below is greater than or equal to the Participation Cost.

Using your Endowment of \$1.50, what is the maximum amount you are willing to pay to participate and fulfill the order on the Platform? (You can use up to two decimal places, e.g., A.BC)

Figure B.4: WTP elicitation screen for intuitive + transparent treatment

We have decided to change our Payment Algorithm

From:

Payment Algorithm: *$[w_1 \text{ x } N_1] + [w_2 \text{ x } N_2] + [w_3 \text{ x } N_3] + [w_4 \text{ x } N_4]$*

To:

Payment Algorithm V2: *$[z_1 \text{ x } N_1] + [z_2 \text{ x } N_2] + [z_3 \text{ x } N_3] + [z_4 \text{ x } N_4]$*

Payment Algorithm V2 will be used to determine your payments on orders hereafter.

Figure B.5: Study 3 Announcement of change in algorithm

B.2 Additional Analysis, Study 3

B.2.1 Drivers of the effect of change in algorithm under transparency and opacity

Here, we explore the reason for the drop in workers' willingness to work for a transparent platform and for the decline in workers' perceptions of an opaque platform following a change from an intuitive to a non-intuitive algorithm. To do this, we divide the change into two categories to capture a worker's experience under the change. Workers who are assigned a difficult order (OC3 or OC4) in the second period, undergo a decrease in financial return on their effort, since the newly introduced non-intuitive algorithm pays less for such orders compared to the previously used intuitive algorithm. In contrast, workers who are assigned an easy order (OC1 or OC1) in the second period, undergo an increase in financial return on their effort. We use $Decrease_i$ and $Increase_i$ to capture these experiences at the individual level. Our empirical approach is similar to the one in Table 3.11, except that now we specify a worker's individual experience under the change. In this analysis, both $Decrease_i$ and $Increase_i$ equal 0 for workers that do not experience an algorithm change.

Results are reported in Table B.2. From the last two rows of column (2), we observe that under transparency, the lower willingness to work for the platform following the change is attributable to workers who experience a decrease in return on their effort under the change. Moreover, the coefficients on the terms *Decrease* and *Increase* in columns (3)-(8) show that when the platform is opaque, workers' poor perceptions following the change are attributable to workers who experience a decrease in return on their effort under the change.

B.2.2 Role of transparency in managing perceptions about the change

Continuing with a similar empirical approach, we study the role of transparency in managing workers' perceptions about the change. Results are reported in Table B.3. In columns (1) and (2), we observe that workers who see a decrease in return on effort under the change on an opaque platform directionally find the change to be less fair and find the newly implemented non-intuitive

Table B.2: Drivers of the effect of change in algorithm under transparency and opacity, Study 3

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Transparent	-0.038	0.098	-0.121	0.409	0.191	0.001	0.001	0.197
	(0.058)	(0.099)	(0.234)	(0.299)	(0.294)	(0.238)	(0.270)	(0.307)
Increase	-0.052	0.194	-0.070	0.030	0.093	-0.439	0.025	-0.072
	(0.074)	(0.126)	(0.301)	(0.385)	(0.379)	(0.307)	(0.348)	(0.396)
Decrease	0.026	-0.200	-1.171***	-1.300***	-1.660***	-0.801***	-1.485***	-1.628***
	(0.074)	(0.125)	(0.296)	(0.378)	(0.372)	(0.301)	(0.341)	(0.388)
Transparent × Increase	0.116	-0.284	-0.059	-0.190	-0.246	0.208	-0.138	-0.227
	(0.103)	(0.176)	(0.421)	(0.538)	(0.529)	(0.428)	(0.487)	(0.553)
Transparent × Decrease	0.076	-0.072	1.225***	1.508***	1.679***	1.186***	1.436***	1.581***
	(0.103)	(0.176)	(0.414)	(0.529)	(0.521)	(0.421)	(0.478)	(0.543)
Difficult_1	0.018	0.048	0.300*	0.267	0.164	0.186	0.178	0.223
	(0.042)	(0.072)	(0.170)	(0.217)	(0.214)	(0.173)	(0.196)	(0.223)
Easy_3			0.583***	0.266	0.356	0.228	0.318	0.253
			(0.206)	(0.263)	(0.259)	(0.209)	(0.238)	(0.270)
Difficult_3			0.257	0.297	0.213	0.221	0.214	0.202
			(0.206)	(0.264)	(0.259)	(0.210)	(0.238)	(0.271)
Constant	0.087**	0.779***	4.859***	4.109***	4.640***	5.208***	4.672***	4.343***
	(0.044)	(0.075)	(0.198)	(0.253)	(0.248)	(0.201)	(0.228)	(0.259)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Decrease +	0.102	-0.272**	0.054	0.208	0.019	0.385	-0.0495	-0.047
(Transparent × Decrease)	(0.072)	(0.123)	(0.290)	(0.370)	(0.364)	(0.295)	(0.335)	(0.380)
Increase +	0.063	-0.091	-0.129	-0.160	-0.154	-0.231	-0.113	-0.299
(Transparent × Increase)	(0.072)	(0.123)	(0.291)	(0.371)	(0.365)	(0.295)	(0.336)	(0.381)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

algorithm to be significantly inappropriate compared to those who see an increase in return on effort, whereas transparency helps workers perceive the change to be more fair comparatively, which is confirmed through a linear hypothesis test on the sum of coefficients on *Decrease* and *Decrease* x *Transparent* demonstrated in the last row of the table. In column (3), we observe that workers do not perceive the pay under the intuitive algorithm to exceed that under the non-intuitive algorithm irrespective of the transparency condition.

Table B.3: Role of transparency in managing perceptions about change, Study 3

	$\text{New}_{\textit{fair}}$ (1)	$\text{New}_{\textit{appropriate}}$ (2)	*Oldpaysmore* (3)
Decrease	-0.730	-0.957**	-0.199
	(0.443)	(0.452)	(0.470)
Transparent	0.135	-0.175	-0.758
	(0.434)	(0.443)	(0.461)
Decrease × Transparent	0.657	0.622	0.556
	(0.605)	(0.617)	(0.642)
Difficult_1	-0.457	-0.541*	0.559*
	(0.305)	(0.312)	(0.324)
Easy_3	0.720*	0.456	-0.049
	(0.374)	(0.382)	(0.397)
Difficult_3	0.329	-0.133	0.467
	(0.372)	(0.380)	(0.395)
Constant	4.315***	4.834***	4.114***
	(0.440)	(0.449)	(0.467)
Observations	97	97	97
Linear Hypotheses Tests:			
Transparent +	-0.072	-0.335	0.358
(Transparent × Decrease)	(0.411)	(0.420)	(0.437)

These perceptions were elicited only from subjects who experienced a change in algorithm. Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

B.3 Controlling for participants' risk aversion and demographics

Since our experimental manipulation of transparency varies the amount of information that participants have about the algorithm, workers' poor perceptions of the platform under an opaque algorithm can potentially be attributed to participants' risk aversion. More generally, one might be concerned that heterogeneity in participant demographics can influence our results. To test for these effects, we run our regression models while controlling for risk aversion and demographic characteristics. In particular, we include the following variables: *Age*$_i$ denotes the participant i's age in years; *Male*$_i$ (*Female*$_i$) equals 1 if the participant self-identifies as a male (female), and 0 otherwise (with other and prefer not to say serving as the baseline for these dummy variables); *Education_college*$_i$ equals 1 for participants with at least a college degree, and 0 otherwise; *Income_high*$_i$ equals for participants with an annual income of $50,000 or more, and 0 otherwise; *Risk-averse*$_i$ equals 1 for participants categorized as being risk averse based on responses in the risk preference elicitation section, and 0 otherwise. As evident from the tables below, our insights continue to hold after controlling for participants' risk preferences and demographics.

Table B.4: Effect of algorithm intuitiveness and transparency, Study 1

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.025	-0.067	-0.244	-0.045	-0.094	-0.007	-0.179	-0.225
	(0.025)	(0.059)	(0.189)	(0.215)	(0.217)	(0.203)	(0.202)	(0.227)
Transparent	-0.019	0.081	0.424**	0.947***	0.729***	0.648***	0.609***	0.678***
	(0.025)	(0.058)	(0.187)	(0.213)	(0.214)	(0.201)	(0.200)	(0.225)
Easy			0.946***	0.792***	0.823***	0.739***	1.094***	1.263***
			(0.220)	(0.251)	(0.252)	(0.236)	(0.235)	(0.265)
Difficult			1.047***	0.894***	0.961***	0.864***	0.982***	1.247***
			(0.269)	(0.307)	(0.308)	(0.288)	(0.288)	(0.323)
Age	0.00003	-0.003	-0.003	-0.011	0.003	0.004	-0.007	-0.005
	(0.001)	(0.003)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)
Male	0.025	0.005	0.825	0.473	1.000	-0.214	0.243	-0.144
	(0.081)	(0.192)	(0.620)	(0.706)	(0.710)	(0.664)	(0.662)	(0.745)
Female	0.023	-0.079	0.617	0.273	0.685	-0.394	0.052	-0.381
	(0.082)	(0.193)	(0.624)	(0.710)	(0.714)	(0.668)	(0.667)	(0.749)
Education_college	-0.053	-0.034	-0.185	-0.426	-0.462	-0.156	-0.251	-0.638
	(0.045)	(0.106)	(0.344)	(0.392)	(0.394)	(0.368)	(0.368)	(0.413)
Income_high	0.053**	-0.051	0.369*	0.290	0.441*	0.277	0.346	0.192
	(0.026)	(0.061)	(0.197)	(0.224)	(0.226)	(0.211)	(0.211)	(0.237)
Risk-averse	0.019	-0.160***	-0.332*	-0.440**	-0.339	-0.009	-0.272	-0.233
	(0.025)	(0.058)	(0.192)	(0.218)	(0.220)	(0.205)	(0.205)	(0.230)
Constant	0.034	1.077***	3.583***	3.799***	3.096***	4.340***	3.841***	4.270***
	(0.097)	(0.230)	(0.753)	(0.857)	(0.862)	(0.806)	(0.804)	(0.904)
Observations	200	200	200	200	200	200	200	200

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.
The variable Age_i denotes the age of participant i. For individual i identifying themselves as a male (female), the variable $Male_i$ ($Female_i$) equals 1, and 0 otherwise. The variable $Education\_college_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable $Income\_high_i$ equals 1 if participant i has an annual income of \$50,000 or more, and 0 otherwise. The variable $Risk\text{-}averse_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.5: Role of transparency in managing engagement under the algorithms, Study 1

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.013	-0.071	-0.406	0.056	-0.122	0.109	-0.120	-0.138
	(0.035)	(0.083)	(0.267)	(0.304)	(0.306)	(0.286)	(0.286)	(0.321)
Transparent	-0.008	0.077	0.260	1.051***	0.701**	0.766***	0.669**	0.766**
	(0.035)	(0.083)	(0.268)	(0.306)	(0.308)	(0.287)	(0.287)	(0.323)
Intuitive × Transparent	-0.022	0.009	0.323	-0.203	0.055	-0.232	-0.119	-0.173
	(0.049)	(0.116)	(0.376)	(0.429)	(0.431)	(0.403)	(0.402)	(0.452)
Easy			0.941***	0.795***	0.823***	0.743***	1.096***	1.266***
			(0.221)	(0.251)	(0.253)	(0.236)	(0.236)	(0.265)
Difficult			1.042***	0.897***	0.960***	0.868***	0.984***	1.250***
			(0.270)	(0.307)	(0.309)	(0.289)	(0.288)	(0.324)
Age	-0.00002	-0.003	-0.002	-0.011	0.003	0.003	-0.007	-0.006
	(0.001)	(0.003)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Male	0.025	0.005	0.822	0.475	0.999	-0.212	0.244	-0.143
	(0.081)	(0.192)	(0.621)	(0.707)	(0.712)	(0.665)	(0.664)	(0.746)
Female	0.024	-0.079	0.599	0.285	0.682	-0.381	0.058	-0.371
	(0.082)	(0.193)	(0.625)	(0.712)	(0.717)	(0.670)	(0.669)	(0.751)
Education_college	-0.052	-0.034	-0.196	-0.420	-0.463	-0.149	-0.247	-0.632
	(0.045)	(0.106)	(0.345)	(0.393)	(0.395)	(0.369)	(0.369)	(0.414)
Income_high	0.052**	-0.051	0.376*	0.285	0.442*	0.272	0.343	0.188
	(0.026)	(0.061)	(0.198)	(0.225)	(0.227)	(0.212)	(0.211)	(0.238)
Risk-averse	0.018	-0.159***	-0.324*	-0.445**	-0.337	-0.015	-0.275	-0.238
	(0.025)	(0.058)	(0.192)	(0.219)	(0.221)	(0.206)	(0.206)	(0.231)
Constant	0.029	1.079***	3.658***	3.752***	3.108***	4.286***	3.814***	4.230***
	(0.098)	(0.232)	(0.759)	(0.864)	(0.870)	(0.813)	(0.811)	(0.912)
Observations	200	200	200	200	200	200	200	200
Linear Hypotheses Tests:								
Transparent +	-0.030	0.086	0.582**	0.848***	0.755**	0.534*	0.551*	0.593*
(Intuitive × Transparent)	(0.035)	(0.081)	(0.263)	(0.300)	(0.302)	(0.282)	(0.281)	(0.316)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.
The variable Age_i denotes the age of participant i. For individual i identifying themselves as a male (female), the variable $Male_i$ ($Female_i$) equals 1, and 0 otherwise. The variable $Education\_college_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable $Income\_high_i$ equals 1 if participant i has an annual income of \$50,000 or more, and 0 otherwise. The variable $Risk\text{-}averse_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.6: Effect of algorithm intuitiveness and transparency, Study 2

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.036	0.132*	0.076	0.238	0.096	0.120	0.132	-0.159
	(0.042)	(0.071)	(0.201)	(0.220)	(0.224)	(0.201)	(0.201)	(0.235)
Transparent	-0.099**	0.093	0.505**	1.078***	0.512**	0.323	0.693***	0.885***
	(0.042)	(0.071)	(0.201)	(0.220)	(0.223)	(0.201)	(0.201)	(0.234)
Difficult_1	-0.042	0.053	0.139	0.068	0.053	0.204	0.076	0.132
	(0.043)	(0.073)	(0.205)	(0.225)	(0.228)	(0.205)	(0.205)	(0.240)
Easy_2			0.917***	0.943***	0.819***	1.011***	0.966***	1.269***
			(0.246)	(0.269)	(0.274)	(0.246)	(0.246)	(0.288)
Difficult_2			0.789***	0.828***	0.857***	0.823***	0.941***	1.146***
			(0.245)	(0.268)	(0.272)	(0.245)	(0.245)	(0.286)
Age	0.001	-0.0003	0.003	-0.014	-0.007	0.001	-0.006	-0.011
	(0.002)	(0.003)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)
Male	-0.179	0.330	0.124	-0.014	-0.135	0.130	0.017	0.072
	(0.125)	(0.213)	(0.604)	(0.661)	(0.671)	(0.604)	(0.603)	(0.705)
Female	-0.221*	0.251	0.347	0.176	-0.018	0.210	0.302	0.164
	(0.125)	(0.213)	(0.604)	(0.661)	(0.671)	(0.604)	(0.603)	(0.705)
Education_college	0.120*	-0.052	-0.905***	-1.142***	-1.088***	-0.851***	-0.931***	-0.937**
	(0.065)	(0.110)	(0.312)	(0.342)	(0.347)	(0.312)	(0.312)	(0.365)
Income_high	-0.114***	0.039	0.882***	0.686***	0.886***	0.829***	0.918***	0.848***
	(0.044)	(0.074)	(0.211)	(0.231)	(0.235)	(0.212)	(0.211)	(0.247)
Risk-averse	0.003	-0.018	-0.325	-0.326	-0.051	-0.234	-0.288	-0.255
	(0.044)	(0.074)	(0.208)	(0.228)	(0.231)	(0.208)	(0.208)	(0.243)
Constant	0.306**	0.425*	4.019***	4.060***	4.371***	4.347***	3.989***	3.714***
	(0.148)	(0.251)	(0.706)	(0.773)	(0.785)	(0.707)	(0.706)	(0.825)
Observations	201	201	201	201	201	201	201	201

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.
The variable Age_i denotes the age of participant i. For individual i identifying themselves as a male (female), the variable $Male_i$ ($Female_i$) equals 1, and 0 otherwise. The variable $Education\_college_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable $Income\_high_i$ equals 1 if participant i has an annual income of \$50,000 or more, and 0 otherwise. The variable $Risk\text{-}averse_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.7: Role of transparency in managing engagement under the algorithms, Study 2

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	-0.063	0.226**	-0.154	0.034	-0.0002	-0.154	-0.138	-0.171
	(0.059)	(0.100)	(0.284)	(0.312)	(0.317)	(0.284)	(0.284)	(0.333)
Transparent	-0.127**	0.192*	0.266	0.866***	0.412	0.038	0.412	0.873**
	(0.061)	(0.102)	(0.290)	(0.318)	(0.323)	(0.289)	(0.289)	(0.340)
Intuitive × Transparent	0.054	-0.188	0.452	0.402	0.189	0.539	0.532	0.022
	(0.083)	(0.141)	(0.396)	(0.434)	(0.441)	(0.395)	(0.395)	(0.464)
Difficult_1	-0.041	0.052	0.141	0.069	0.054	0.206	0.078	0.132
	(0.043)	(0.073)	(0.205)	(0.225)	(0.229)	(0.205)	(0.205)	(0.240)
Easy_2			0.934***	0.958***	0.826***	1.031***	0.986***	1.270***
			(0.246)	(0.270)	(0.275)	(0.246)	(0.246)	(0.289)
Difficult_2			0.797***	0.835***	0.861***	0.833***	0.951***	1.146***
			(0.245)	(0.268)	(0.273)	(0.245)	(0.244)	(0.287)
Age	0.001	-0.0001	0.003	-0.015	-0.007	0.001	-0.007	-0.011
	(0.002)	(0.003)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)
Male	-0.179	0.329	0.122	-0.016	-0.136	0.127	0.015	0.071
	(0.126)	(0.212)	(0.603)	(0.661)	(0.672)	(0.603)	(0.602)	(0.707)
Female	-0.219*	0.242	0.361	0.189	-0.012	0.227	0.319	0.165
	(0.126)	(0.213)	(0.603)	(0.661)	(0.673)	(0.603)	(0.602)	(0.707)
Education_college	0.118*	-0.046	-0.919***	-1.155***	-1.094***	-0.869***	-0.948***	-0.938**
	(0.065)	(0.110)	(0.312)	(0.342)	(0.348)	(0.312)	(0.312)	(0.366)
Income_high	-0.115***	0.041	0.875***	0.680***	0.883***	0.822***	0.910***	0.848***
	(0.044)	(0.074)	(0.211)	(0.232)	(0.236)	(0.211)	(0.211)	(0.248)
Risk-averse	0.003	-0.017	-0.326	-0.326	-0.051	-0.235	-0.288	-0.255
	(0.044)	(0.074)	(0.208)	(0.228)	(0.232)	(0.208)	(0.207)	(0.244)
Constant	0.323**	0.363	4.167***	4.191***	4.433***	4.523***	4.162***	3.722***
	(0.151)	(0.255)	(0.717)	(0.786)	(0.800)	(0.717)	(0.716)	(0.841)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Transparent +	-0.073	0.004	0.718***	1.268***	0.601*	0.577**	0.943***	0.895***
(Intuitive × Transparent)	(0.058)	(0.097)	(0.274)	(0.300)	(0.305)	(0.274)	(0.273)	(0.321)
Intuitive +	-0.009	0.039	0.299	0.435	0.189	0.386	0.393	-0.149
(Intuitive × Transparent)	(0.059)	(0.099)	(0.280)	(0.307)	(0.312)	(0.280)	(0.279)	(0.328)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.
The variable *Age*$_i$ denotes the age of participant i. For individual i identifying themselves as a male (female), the variable *Male*$_i$ (*Female*$_i$) equals 1, and 0 otherwise. The variable *Education_college*$_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable *Income_high*$_i$ equals 1 if participant i has an annual income of $50,000 or more, and 0 otherwise. The variable *Risk-averse*$_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.8: Role of transparency in managing the effect of experience, Study 2

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Intuitive	0.056	0.062	-0.304	0.065	-0.290	-0.364	-0.401	-0.618
	(0.071)	(0.120)	(0.343)	(0.377)	(0.382)	(0.342)	(0.342)	(0.399)
Transparent	-0.158**	0.154	0.271	0.775**	0.470	0.149	0.377	0.790*
	(0.071)	(0.122)	(0.349)	(0.383)	(0.388)	(0.348)	(0.347)	(0.406)
Difficult_1	0.059	-0.173	-0.029	0.008	-0.222	0.078	-0.266	-0.480
	(0.074)	(0.126)	(0.359)	(0.394)	(0.399)	(0.358)	(0.357)	(0.417)
Intuitive × Transparent	0.057	-0.193	0.446	0.400	0.178	0.533	0.519	-0.0003
	(0.082)	(0.139)	(0.397)	(0.436)	(0.441)	(0.396)	(0.395)	(0.461)
Transparent × Difficult_1	0.055	0.092	0.009	0.186	-0.084	-0.203	0.107	0.233
	(0.083)	(0.141)	(0.402)	(0.442)	(0.447)	(0.401)	(0.400)	(0.467)
Intuitive × Difficult_1	-0.242***	0.338**	0.319	-0.063	0.611	0.442	0.557	0.950**
	(0.082)	(0.139)	(0.404)	(0.443)	(0.449)	(0.403)	(0.402)	(0.469)
Easy_2			0.912***	0.967***	0.783***	0.996***	0.951***	1.211***
			(0.249)	(0.273)	(0.277)	(0.248)	(0.248)	(0.289)
Difficult_2			0.762***	0.846***	0.791***	0.779***	0.891***	1.046***
			(0.250)	(0.274)	(0.278)	(0.249)	(0.248)	(0.290)
Age	0.001	-0.0004	0.002	-0.014	-0.008	-0.0003	-0.008	-0.012
	(0.002)	(0.003)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)
Male	-0.166	0.283	0.103	-0.046	-0.154	0.140	-0.034	-0.022
	(0.124)	(0.212)	(0.610)	(0.670)	(0.678)	(0.608)	(0.607)	(0.708)
Female	-0.215*	0.197	0.346	0.146	-0.015	0.260	0.271	0.069
	(0.125)	(0.213)	(0.614)	(0.674)	(0.682)	(0.612)	(0.610)	(0.713)
Education_college	0.133**	-0.060	-0.941***	-1.142***	-1.140***	-0.908***	-0.981***	-0.992***
	(0.064)	(0.109)	(0.315)	(0.346)	(0.350)	(0.314)	(0.313)	(0.366)
Income_high	-0.110**	0.037	0.874***	0.683***	0.879***	0.817***	0.908***	0.845***
	(0.043)	(0.073)	(0.212)	(0.233)	(0.236)	(0.211)	(0.211)	(0.246)
Risk-averse	0.001	-0.019	-0.325	-0.333	-0.046	-0.226	-0.290	-0.259
	(0.043)	(0.073)	(0.209)	(0.229)	(0.232)	(0.208)	(0.208)	(0.243)
Constant	0.239	0.541**	4.312***	4.228***	4.676***	4.649***	4.448***	4.228***
	(0.155)	(0.264)	(0.756)	(0.830)	(0.840)	(0.754)	(0.752)	(0.878)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Transparent+	-0.103	0.246*	0.280	0.961**	0.387	-0.054	0.484	1.023**
(Transparent × Difficult_1)	(0.074)	(0.125)	(0.358)	(0.393)	(0.398)	(0.357)	(0.356)	(0.416)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.
The variable Age_i denotes the age of participant i. For individual i identifying themselves as a male (female), the variable $Male_i$ ($Female_i$) equals 1, and 0 otherwise. The variable $Education\_college_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable $Income\_high_i$ equals 1 if participant i has an annual income of \$50,000 or more, and 0 otherwise. The variable $Risk\text{-}averse_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.9: Effect of Change, Study 3

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Transparent	0.022	0.009	0.130	0.763***	0.500**	0.278	0.278	0.502**
	(0.043)	(0.075)	(0.175)	(0.222)	(0.221)	(0.179)	(0.202)	(0.229)
Change	0.046	-0.097	-0.340*	-0.288	-0.425*	-0.251	-0.416**	-0.500**
	(0.043)	(0.075)	(0.173)	(0.219)	(0.219)	(0.177)	(0.200)	(0.227)
Difficult_1	0.016	0.047	0.190	0.120	0.027	0.128	0.039	0.108
	(0.043)	(0.075)	(0.175)	(0.222)	(0.221)	(0.179)	(0.202)	(0.229)
Difficult_2	0.007	-0.082	-0.229	-0.399*	-0.562**	-0.107	-0.391*	-0.396*
	(0.043)	(0.074)	(0.172)	(0.218)	(0.218)	(0.176)	(0.199)	(0.226)
Easy_3			0.665***	0.394	0.495*	0.243	0.428*	0.368
			(0.207)	(0.261)	(0.261)	(0.211)	(0.238)	(0.271)
Difficult_3			0.317	0.391	0.315	0.220	0.309	0.343
			(0.208)	(0.262)	(0.262)	(0.212)	(0.239)	(0.272)
Age	0.002	-0.003	-0.0003	0.004	-0.005	-0.005	-0.00001	0.005
	(0.002)	(0.003)	(0.007)	(0.009)	(0.009)	(0.007)	(0.008)	(0.009)
Male	0.122	0.047	0.037	0.906	0.055	-0.404	-0.248	-0.700
	(0.178)	(0.310)	(0.726)	(0.918)	(0.917)	(0.740)	(0.837)	(0.950)
Female	0.111	0.062	0.113	0.851	0.024	-0.433	-0.222	-0.872
	(0.179)	(0.311)	(0.728)	(0.921)	(0.920)	(0.743)	(0.840)	(0.953)
Education_college	-0.078	0.061	-0.431	-1.014***	-0.770**	-0.308	-0.746**	-0.862**
	(0.065)	(0.113)	(0.264)	(0.334)	(0.333)	(0.269)	(0.304)	(0.346)
Income_high	-0.008	-0.069	0.484**	0.412*	0.484**	0.283	0.596***	0.511**
	(0.046)	(0.080)	(0.187)	(0.236)	(0.236)	(0.190)	(0.215)	(0.244)
Risk-averse	0.052	-0.087	0.262	0.100	0.101	0.234	0.169	0.166
	(0.044)	(0.076)	(0.178)	(0.225)	(0.225)	(0.181)	(0.205)	(0.233)
Constant	-0.103	0.973***	4.738***	3.671***	5.226***	5.698***	5.170***	5.312***
	(0.198)	(0.345)	(0.814)	(1.029)	(1.028)	(0.830)	(0.939)	(1.066)
Observations	201	201	201	201	201	201	201	201

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

The variable Age_i denotes the age of participant i. For individual i identifying themselves as a male (female), the variable $Male_i$ ($Female_i$) equals 1, and 0 otherwise. The variable $Education\_college_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable $Income\_high_i$ equals 1 if participant i has an annual income of \$50,000 or more, and 0 otherwise. The variable $Risk\text{-}averse_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.10: Effect of transparency in managing engagement under change, Study 3

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Transparent	-0.027	0.094	-0.169	0.423	0.118	-0.093	-0.060	0.148
	(0.060)	(0.105)	(0.243)	(0.307)	(0.306)	(0.246)	(0.280)	(0.318)
Change	-0.003	-0.011	-0.644***	-0.633**	-0.813***	-0.628**	-0.759***	-0.859***
	(0.060)	(0.105)	(0.243)	(0.308)	(0.307)	(0.247)	(0.280)	(0.319)
Transparent × Change	0.099	-0.174	0.613*	0.696	0.783*	0.761**	0.692*	0.724
	(0.085)	(0.149)	(0.346)	(0.438)	(0.436)	(0.351)	(0.399)	(0.453)
Difficult_1	0.023	0.036	0.231	0.166	0.079	0.179	0.084	0.156
	(0.044)	(0.076)	(0.176)	(0.223)	(0.222)	(0.179)	(0.203)	(0.230)
Difficult_2	0.008	-0.083	-0.223	-0.392*	-0.554**	-0.100	-0.384*	-0.389*
	(0.042)	(0.074)	(0.171)	(0.217)	(0.216)	(0.174)	(0.198)	(0.225)
Easy_3			0.692***	0.425	0.530**	0.277	0.458*	0.401
			(0.206)	(0.261)	(0.260)	(0.209)	(0.238)	(0.270)
Difficult_3			0.344*	0.421	0.348	0.253	0.339	0.374
			(0.207)	(0.262)	(0.261)	(0.210)	(0.239)	(0.271)
Age	0.002	-0.003	-0.001	0.003	-0.006	-0.006	-0.001	0.004
	(0.002)	(0.003)	(0.007)	(0.009)	(0.009)	(0.007)	(0.008)	(0.009)
Male	0.112	0.065	-0.020	0.841	-0.018	-0.475	-0.312	-0.767
	(0.178)	(0.310)	(0.723)	(0.915)	(0.912)	(0.734)	(0.833)	(0.947)
Female	0.105	0.073	0.076	0.808	-0.024	-0.479	-0.264	-0.916
	(0.179)	(0.311)	(0.725)	(0.918)	(0.915)	(0.736)	(0.836)	(0.950)
Education_college	-0.081	0.068	-0.455*	-1.042***	-0.801**	-0.339	-0.774**	-0.891**
	(0.065)	(0.114)	(0.263)	(0.333)	(0.332)	(0.267)	(0.303)	(0.345)
Income_high	-0.011	-0.064	0.465**	0.390*	0.459*	0.259	0.574***	0.488**
	(0.046)	(0.080)	(0.186)	(0.236)	(0.235)	(0.189)	(0.215)	(0.244)
Risk-averse	0.054	-0.090	0.273	0.113	0.116	0.248	0.182	0.180
	(0.044)	(0.076)	(0.177)	(0.224)	(0.223)	(0.180)	(0.204)	(0.232)
Constant	-0.064	0.906**	4.953***	3.915***	5.501***	5.965***	5.413***	5.566***
	(0.201)	(0.349)	(0.819)	(1.037)	(1.034)	(0.831)	(0.944)	(1.073)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Change +	0.095	-0.185*	-0.031	0.063	-0.031	0.132	-0.068	-0.135
(Transparent × Change)	(0.061)	(0.106)	(0.245)	(0.310)	(0.310)	(0.249)	(0.283)	(0.321)
Transparent +	0.072	-0.080	0.443*	1.120***	0.900***	0.668***	0.632**	0.872***
(Transparent × Change)	(0.061)	(0.107)	(0.248)	(0.315)	(0.314)	(0.252)	(0.287)	(0.326)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

The variable Age_i denotes the age of participant i. For individual i identifying themselves as a male (female), the variable $Male_i$ ($Female_i$) equals 1, and 0 otherwise. The variable $Education\_college_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable $Income\_high_i$ equals 1 if participant i has an annual income of \$50,000 or more, and 0 otherwise. The variable $Risk\text{-}averse_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.11: Role of transparency in managing the effect of experience under change, Study 3

	Reject (1)	WTP (2)	Trust (3)	Sincerity (4)	Fairness (5)	Info-correctness (6)	Favorability (7)	Work-attractiveness (8)
Transparent	-0.026	0.091	-0.183	0.401	0.091	-0.107	-0.079	0.127
	(0.060)	(0.103)	(0.238)	(0.304)	(0.300)	(0.244)	(0.274)	(0.312)
Decrease	0.038	-0.210	-1.172***	-1.229***	-1.643***	-0.805***	-1.470***	-1.589***
	(0.074)	(0.127)	(0.294)	(0.375)	(0.371)	(0.301)	(0.338)	(0.386)
Increase	-0.045	0.189	-0.086	-0.004	0.060	-0.437	-0.011	-0.088
	(0.075)	(0.128)	(0.299)	(0.382)	(0.378)	(0.307)	(0.345)	(0.393)
Transparent × Decrease	0.081	-0.071	1.262***	1.521***	1.750***	1.301***	1.473***	1.620***
	(0.106)	(0.181)	(0.418)	(0.533)	(0.527)	(0.428)	(0.480)	(0.548)
Transparent × Increase	0.118	-0.280	-0.050	-0.126	-0.193	0.241	-0.108	-0.185
	(0.104)	(0.178)	(0.418)	(0.533)	(0.527)	(0.428)	(0.481)	(0.548)
Difficult_1	0.019	0.048	0.251	0.171	0.088	0.175	0.104	0.175
	(0.044)	(0.075)	(0.172)	(0.220)	(0.217)	(0.176)	(0.198)	(0.226)
Easy_3			0.591***	0.308	0.375	0.229	0.326	0.261
			(0.205)	(0.262)	(0.259)	(0.210)	(0.236)	(0.269)
Difficult_3			0.243	0.313	0.201	0.214	0.209	0.239
			(0.206)	(0.263)	(0.260)	(0.211)	(0.237)	(0.270)
Age	0.002	-0.003	-0.002	0.003	-0.006	-0.006	-0.002	0.003
	(0.002)	(0.003)	(0.007)	(0.009)	(0.009)	(0.007)	(0.008)	(0.009)
Male	0.106	0.079	-0.124	0.669	-0.197	-0.625	-0.434	-0.924
	(0.179)	(0.306)	(0.711)	(0.908)	(0.898)	(0.729)	(0.818)	(0.933)
Female	0.104	0.074	-0.003	0.690	-0.152	-0.572	-0.358	-1.032
	(0.179)	(0.306)	(0.712)	(0.909)	(0.899)	(0.729)	(0.819)	(0.934)
Education_college	-0.088	0.096	-0.415	-1.014***	-0.744**	-0.360	-0.715**	-0.840**
	(0.066)	(0.112)	(0.259)	(0.331)	(0.327)	(0.266)	(0.298)	(0.340)
Income_high	-0.012	-0.061	0.452**	0.371	0.444*	0.235	0.563***	0.470*
	(0.046)	(0.079)	(0.183)	(0.233)	(0.231)	(0.187)	(0.210)	(0.240)
Risk-averse	0.053	-0.083	0.306*	0.159	0.173	0.274	0.226	0.228
	(0.044)	(0.075)	(0.174)	(0.222)	(0.219)	(0.178)	(0.200)	(0.228)
Constant	-0.049	0.822**	4.959***	3.910***	5.409***	6.102***	5.348***	5.544***
	(0.201)	(0.344)	(0.805)	(1.028)	(1.016)	(0.825)	(0.926)	(1.056)
Observations	201	201	201	201	201	201	201	201
Linear Hypotheses Tests:								
Decrease +	0.120	-0.281**	0.090	0.292	0.107	0.497	0.002	0.031
(Transparent × Decrease)	(0.076)	(0.129)	(0.299)	(0.381)	(0.377)	(0.306)	(0.344)	(0.392)
Increase +	0.073	-0.091	-0.136	-0.130	-0.133	-0.197	-0.119	-0.274
(Transparent × Increase)	(0.073)	(0.125)	(0.290)	(0.370)	(0.366)	(0.297)	(0.333)	(0.380)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

The variable Age_i denotes the age of participant i. For individual i identifying themselves as a male (female), the variable $Male_i$ ($Female_i$) equals 1, and 0 otherwise. The variable $Education\_college_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable $Income\_high_i$ equals 1 if participant i has an annual income of \$50,000 or more, and 0 otherwise. The variable $Risk\text{-}averse_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

Table B.12: Role of transparency in managing perceptions about change, Study 3

	New$_{fair}$ (1)	New$_{appropriate}$ (2)	*Oldpaysmore* (3)
Decrease	-0.755	-1.019**	-0.230
	(0.459)	(0.460)	(0.478)
Transparent	0.048	-0.255	-0.848*
	(0.452)	(0.452)	(0.470)
Decrease × Transparent	0.739	0.713	0.550
	(0.629)	(0.630)	(0.655)
Difficult$_1$	-0.473	-0.538*	0.413
	(0.321)	(0.321)	(0.334)
Easy$_3$	0.701*	0.452	-0.153
	(0.388)	(0.388)	(0.404)
Difficult$_3$	0.319	-0.137	0.356
	(0.385)	(0.385)	(0.400)
Age	-0.005	0.003	-0.024*
	(0.013)	(0.013)	(0.013)
Male	-0.419	-0.121	1.858
	(1.565)	(1.566)	(1.629)
Female	-0.168	0.144	2.019
	(1.561)	(1.562)	(1.625)
Education_college	0.116	0.265	-0.056
	(0.552)	(0.552)	(0.574)
Income_high	0.231	0.322	0.362
	(0.341)	(0.342)	(0.355)
Risk-averse	0.235	0.606*	-0.118
	(0.318)	(0.319)	(0.332)
Constant	4.490**	4.002**	3.179*
	(1.706)	(1.708)	(1.776)
Observations	97	97	97
Linear Hypotheses Tests:			
Transparent +	-0.015	-0.306	0.320
(Transparent × Decrease)	(0.442)	(0.443)	(0.461)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

The variable *Age*$_i$ denotes the age of participant i. For individual i identifying themselves as a male (female), the variable *Male*$_i$ (*Female*$_i$) equals 1, and 0 otherwise. The variable *Education_college*$_i$ equals 1 if participant i is at least a college graduate, and 0 otherwise. The variable *Income_high*$_i$ equals 1 if participant i has an annual income of $50,000 or more, and 0 otherwise. The variable *Risk-averse*$_i$ equals 1 if participant i can be categorized as being risk averse, and 0 otherwise.

BIBLIOGRAPHY

Afeche P, Liu Z, Maglaras C (2022) Ride-hailing networks with strategic drivers: The impact of platform control capabilities on performance. *Rotman School of Management Working Paper* (3120544):18–19.

Akerlof GA, Yellen JL (1990) The fair wage-effort hypothesis and unemployment. *The Quarterly Journal of Economics* 105(2):255–283.

Allon G, Cohen MC, Sinchaisri WP (2018) The impact of behavioral and economic drivers on gig economy workers. *Available at SSRN 3274628* .

Allyn B (2021) Lyft and uber prices are high. wait times are long and drivers are scarce. https://www.npr.org/2021/08/07/1025534409/lyft-and-uber-prices-are-high-wait-times-are-long-and-drivers-are-scarce.

Amazon Flex (2022) This is how amazon flex works. https://flex.amazon.com/lets-drive.

Arvan M, Fahimnia B, Reisi M, Siemsen E (2019) Integrating human judgement into quantitative forecasting methods: A review. *Omega* 86:237–252.

Avedian S (2022) What is uber's trip radar? https://therideshareguy.com/uber-trip-radar/.

Bai B, Dai H, Zhang DJ, Zhang F, Hu H (2022) The impacts of algorithmic work assignment on fairness perceptions and productivity: Evidence from field experiments. *Manufacturing & Service Operations Management* .

Bai J, So KC, Tang CS, Chen X, Wang H (2019) Coordinating supply and demand on an on-demand service platform with impatient customers. *Manufacturing & Service Operations Management* 21(3):556–570.

Banerjee S, Freund D, Lykouris T (2022) Pricing and optimization in shared vehicle systems: An approximation framework. *Operations Research* 70(3):1783–1805.

Bastani H, Bastani O, Sinchaisri WP (2021) Improving human decision-making with machine learning. *arXiv preprint arXiv:2108.08454* .

Becker GM, DeGroot MH, Marschak J (1964) Measuring utility by a single-response sequential method. *Behavioral science* 9(3):226–232.

Becker-Peth M, Katok E, Thonemann UW (2013) Designing buyback contracts for irrational but predictable newsvendors. *Management Science* 59(8):1800–1816.

Beer R, Rios I, Saban D (2021) Increased transparency in procurement: The role of peer effects. *Management Science* 67(12):7511–7534.

Bellon T (2022) Exclusive uber revamps driver pay algorithm in large u.s. pilot to attract drivers. https://www.reuters.com/business/autos-transportation/exclusive-uber-revamps-driver-pay-algorithm-large-us-pilot-attract-drivers-2022-02-26/.

Benjaafar S, Hu M (2020) Operations management in the age of the sharing economy: What is old and what is new? *Manufacturing & Service Operations Management* 22(1):93–101.

Bernstein ES (2017) Making transparency transparent: The evolution of observation in management theory. *Academy of Management Annals* 11(1):217–266.

Besbes O, Castro F, Lobel I (2021) Surge pricing and its spatial supply response. *Management Science* 67(3):1350–1367.

Bhattarai A (2019) 'don't game my paycheck': Delivery workers say they're being squeezed by ever-changing algorithms. https://www.washingtonpost.com/business/2019/11/07/dont-game-my-paycheck-delivery-workers-say-theyre-being-squeezed-by-ever-changing-algorithms/.

Bimpikis K, Candogan O, Saban D (2019) Spatial pricing in ride-sharing networks. *Operations Research* 67(3):744–769.

Bolt (2021) Bolt commission. https://support.taxify.eu/hc/en-us/articles/115002946374-Bolt-commission.

Borak M (2022) China's gig workers are challenging their algorithmic bosses. https://www.wired.com/story/chinas-gig-workers-challenging-algorithmic-bosses/.

Bradshaw T, Lee D (2022) Is uber's driver shortage finally over? https://www.ft.com/content/1056a50b-84a8-4361-83f2-80eecd0fe79f.

Bray RL (2020) Operational transparency: Showing when work gets done. *Manufacturing & Service Operations Management* .

Buell RW (2021) Last-place aversion in queues. *Management Science* 67(3):1430–1452.

Buell RW, Kalkanci B (2021) How transparency into internal and external responsibility initiatives influences consumer choice. *Management Science* 67(2):932–950.

Buell RW, Kim T, Tsay CJ (2017) Creating reciprocal value through operational transparency. *Management Science* 63(6):1673–1695.

Buell RW, Norton MI (2011) The labor illusion: How operational transparency increases perceived value. *Management Science* 57(9):1564–1579.

Buell RW, Porter E, Norton MI (2021) Surfacing the submerged state: Operational transparency increases trust in and engagement with government. *Manufacturing & Service Operations Management* 23(4):781–802.

Cachon GP, Daniels KM, Lobel R (2017) The role of surge pricing on a service platform with self-scheduling capacity. *Manufacturing & Service Operations Management* 19(3):368–384.

Cachon GP, Fisher M (2000) Supply chain inventory management and the value of shared information. *Management science* 46(8):1032–1048.

Campbell H (2016) Advice for new uber drivers – don't chase the surge! https://maximumridesharingprofits.com/advice-new-uber-drivers-dont-chase-surge/.

Caro F, de Tejada Cuenca AS (2018) Believing in analytics: Managers adherence to price recommendations from a dss. Technical report, Working Paper.

Castillo JC, Knoepfle D, Weyl G (2017) Surge pricing solves the wild goose chase. *Proceedings of the 2017 ACM Conference on Economics and Computation*, 241–242.

Central Digital and Data Office (2021) Uk government publishes pioneering standard for algorithmic transparency. https://www.gov.uk/government/news/uk-government-publishes-pioneering-standard-for-algorithmic-transparency.

Changeorg (2022) Stop hiding pay information from gig workers. https://www.change.org/p/stop-hiding-pay-information-from-gig-workers.

Chaudhuri A, Holbrook MB (2001) The chain of effects from brand trust and brand affect to brand performance: the role of brand loyalty. *Journal of marketing* 65(2):81–93.

Chen L, Lee HL (2009) Information sharing and order variability control under a generalized demand model. *Management science* 55(5):781–797.

Chen L, Mislove A, Wilson C (2015) Peeking beneath the hood of uber. *Proceedings of the 2015 internet measurement conference*, 495–508.

Chen MK, Sheldon M (2016) Dynamic pricing in a labor market: Surge pricing and flexible work on the uber platform. *Ec* 16:455.

Chen Y, Hu M (2020) Pricing and matching with forward-looking buyers and sellers. *Manufacturing & Service Operations Management* 22(4):717–734.

Core JE (2001) A review of the empirical disclosure literature: discussion. *Journal of accounting and economics* 31(1-3):441–456.

Coworkerorg (2020) Data shows shipt's "black-box" algorithm reduces pay of 40% of workers. https://home.coworker.org/data-shows-shipts-black-box-algorithm-reduces-pay-of-40-of-workers/.

Cox K (2019) Uber's and lyft's cut of fares can exceed 50%, report finds. https://arstechnica.com/tech-policy/2019/08/uber-and-lyfts-cut-of-fares-can-exceed-50-report-finds/.

Cramer J, Krueger AB (2016) Disruptive change in the taxi business: The case of uber. *American Economic Review* 106(5):177–182.

Cui R, Allon G, Bassamboo A, Van Mieghem JA (2015) Information sharing in supply chains: An empirical and theoretical valuation. *Management Science* 61(11):2803–2824.

Curchod C, Patriotta G, Cohen L, Neysen N (2020) Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly* 65(3):644–676.

Deci EL, Ryan RM (2000) The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological inquiry* 11(4):227–268.

Dholakia UM (2015) Everyone hates uber's surge pricing–here's how to fix it. *Harvard Business Review* 21(December).

Diakopoulus N (2015) How uber surge pricing really works. https://www.washingtonpost.com/news/wonk/wp/2015/04/17/how-uber-surge-pricing-really-works/.

DiDi (2021) Fee schedule. https://web.didiglobal.com/au/legal/fee-schedule/.

Dietvorst BJ, Simmons JP, Massey C (2015) Algorithm aversion: people erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General* 144(1):114.

Dietvorst BJ, Simmons JP, Massey C (2018) Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science* 64(3):1155–1170.

Doordash (2020) How to use the dash now home page. https://help.doordash.com/dashers/s/article/How-to-use-the-Dash-Now-home-page?language=en_US.

Duggan J, Sherman U, Carbery R, McDonnell A (2020) Algorithmic management and app-work in the gig economy: A research agenda for employment relations and hrm. *Human Resource Management Journal* 30(1):114–132.

Falk A, Fehr E, Zehnder C (2006) Fairness perceptions and reservation wages—the behavioral effects of minimum wage laws. *The Quarterly Journal of Economics* 121(4):1347–1381.

Falk A, Fischbacher U (2006) A theory of reciprocity. *Games and economic behavior* 54(2):293–315.

Fehr E, Gächter S (2000) Fairness and retaliation: The economics of reciprocity. *Journal of economic perspectives* 14(3):159–182.

Fen-Cheng S (2019) Commentary: Shortening the waiting time for your cab with a driver guidance system. https://www.wired.com/2015/10/uberredesign/.

Financial Panther (2021) Shipt shopper app: My grocery delivery side hustle. https://financialpanther.com/shipt-shopper-app/.

Fischels J (2021) Why doordash drivers are on strike. https://www.npr.org/2021/07/31/1023265561/why-doordash-drivers-are-on-strike.

Freund RJ, Wilson WJ, Sa P (2006) *Regression analysis* (Elsevier).

Gaur V, Giloni A, Seshadri S (2005) Information sharing in a supply chain under arma demand. *Management science* 51(6):961–969.

Gavirneni S, Kapuscinski R, Tayur S (1999) Value of information in capacitated supply chains. *Management science* 45(1):16–24.

Gill D, Prowse VL (2011) A novel computerized real effort task based on sliders. *Available at SSRN 1732324* .

Gordon A (2019) ’i wonder what they are hiding:’ lyft drivers can no longer see how much riders paid for each trip. https://jalopnik.com/i-wonder-what-they-are-hiding-lyft-drivers-can-no-long-1839224300.

Grab (2022) Grab faq’s. https://www.grab.com/sg/driver/transport/car/faq/.

Gridwise (2017) Why you should never chase surges (and what to do instead). https://gridwise.io/blog/rideshare/why-you-should-never-chase-surges-and-what-to-do-instead/.

Gridwise (2018) This is how drivers feel about uber’s new driver app. https://gridwise.io/this-is-how-drivers-feel-about-ubers-new-driver-app.

Griesbach K, Reich A, Elliott-Negri L, Milkman R (2019) Algorithmic control in platform food delivery work. *Socius* 5:2378023119870041.

Griffith E (2022) Meet the app that helps gig workers know how much they really make. https://www.nytimes.com/2022/10/11/technology/gig-workers-drivers-para-app.html.

Guda H, Subramanian U (2019) Your uber is arriving: Managing on-demand workers through surge pricing, forecast communication, and worker incentives. *Management Science* 65(5):1995–2014.

Gurvich I, Lariviere M, Moreno A (2019) Operations in the on-demand economy: Staffing services with self-scheduling capacity. *Sharing Economy: Making Supply Meet Demand* 249–278.

Güth W, Schmittberger R, Schwarze B (1982) An experimental analysis of ultimatum bargaining. *Journal of economic behavior & organization* 3(4):367–388.

Healy PM, Palepu KG (2001) Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of accounting and economics* 31(1-3):405–440.

Helling B (2023) What are lyft power zones and how do they work? https://www.ridester.com/lyft-power-zones/#:~:text=These%20zones%20will%20show%20up,you%20can%20get%20a%20bonus.

Hendriks A (2012) Sophie-software platform for human interaction experiments. *University of Osnabrück, Osnabrück* .

Higgins S (2022) Ftc to use algorithms in bid to hobble gig economy. https://cei.org/blog/ftc-to-use-algorithms-in-bid-to-hobble-gig-economy/.

Ho TH, Zhang J (2008) Designing pricing contracts for boundedly rational customers: Does the framing of the fixed fee matter? *Management science* 54(4):686–700.

Holt CA, Laury SK (2002) Risk aversion and incentive effects. *American economic review* 92(5):1644–1655.

Hu B, Hu M, Zhu H (2022) Surge pricing and two-sided temporal responses in ride hailing. *Manufacturing & Service Operations Management* 24(1):91–109.

Hu M, Zhou Y (2020) Price, wage, and fixed commission in on-demand matching. *Available at SSRN 2949513* .

Hub LT (2019) Find high demand with personal power zones. https://www.lyft.com/hub/posts/personal-power-zones.

Hussain S (2020) Target-owned shipt sparks worker protest with pay change. https://www.latimes.com/business/technology/story/2020-07-20/shipt-shoppers-protest-pay-algorithm-change.

Ibrahim R, Kim SH, Tong J (2021) Eliciting human judgment for prediction algorithms. *Management Science* 67(4):2314–2325.

Jha SS, CHENG SF, LOWALEKAR M, WONG N, RAJENDRAM R, VARAKANTHAM P, TROUNG NT, BIN ABD RAHMAN F (2018) A driver guidance system for taxis in singapore.(2018). *AAMAS'18: Proceedings of the 17th International Conference on Autonomous Agents and Multiagent Systems, Stockholm, July 10*, volume 15, 1820–1822.

Jiang ZZ, Kong G, Zhang Y (2021) Making the most of your regret: Workers' relocation decisions in on-demand platforms. *Manufacturing & Service Operations Management* 23(3):695–713.

Kahneman D, Tversky A (1979) Prospect theory: An analysis of decision under risk. *Econometrica* 47(2):263–291, ISSN 00129682, 14680262.

Kalin S (2022) Dubai deliveroo drivers protest pay cut in rare strike. https://www.wsj.com/articles/dubai-deliveroo-drivers-protest-pay-cut-in-rare-strike-11651478251.

Kaori Gurley L (2020) Target's delivery app workers to be paid by a blackbox algorithm nationwide. https://www.vice.com/en/contributor/lauren-kaori-gurley.

Kaori Gurley L (2021) Instacart shoppers will stage nationwide strike. https://www.vice.com/en/article/v7e9gb/instacart-shoppers-will-stage-nationwide-strike.

Kaori Gurley L (2021) Walmart's gig workers are struggling to survive. https://www.vice.com/en/article/4avyzq/walmarts-gig-workers-are-struggling-to-survive.

Karacaoglu N, Moreno A, Ozkan C (2018) Strategically giving service: The effect of real-time information on service efficiency. *Available at SSRN 3260035* .

Kellogg KC, Valentine MA, Christin A (2020) Algorithms at work: The new contested terrain of control. *Academy of Management Annals* 14(1):366–410.

Kerr D (2022) Secretive algorithm will now determine uber driver pay in many cities. https://themarkup.org/working-for-an-algorithm/2022/03/01/secretive-algorithm-will-now-determine-uber-driver-pay-in-many-cities.

Kizilcec RF (2016) How much information? effects of transparency on trust in an algorithmic interface. *Proceedings of the 2016 CHI conference on human factors in computing systems*, 2390–2395.

Kraft T, Valdés L, Zheng Y (2018) Supply chain visibility and social responsibility: Investigating consumers' behaviors and motives. *Manufacturing & Service Operations Management* 20(4):617–636.

Lee HL, So KC, Tang CS (2000) The value of information sharing in a two-level supply chain. *Management science* 46(5):626–643.

Lee HL, Whang S (2000) Information sharing in a supply chain. *International journal of manufacturing technology and management* 1(1):79–93.

Lee MK, Kusbit D, Metsky E, Dabbish L (2015) Working with machines: The impact of algorithmic and data-driven management on human workers. *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, 1603–1612.

Lehdonvirta V (2018) Flexibility in the gig economy: managing time on three online piecework platforms. *New Technology, Work and Employment* 33(1):13–29.

Lehmann CA, Haubitz CB, Fügener A, Thonemann UW (2022) The risk of algorithm transparency: How algorithm complexity drives the effects on the use of advice. *Production and Operations Management* 31(9):3419–3434.

Lemar P (2022) Uber upfront pricing makes a move into new markets. https://therideshareguy.com/upfront-pricing-for-drivers/.

Leuz C, Wysocki PD (2016) The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of accounting research* 54(2):525–622.

Levitin AJ (2013) The disclosure paradigm. presentation at the georgetown university law center.

Li L (2002) Information sharing in a supply chain with horizontal competition. *Management Science* 48(9):1196–1212.

Lomas N (2021) Europe lays out a plan to flip the odds on gig economy exploitation. https://techcrunch.com/2021/12/09/eu-gig-economy-proposal/.

Long X, Nasiry J (2020) Wage transparency and social comparison in sales force compensation. *Management Science* 66(11):5290–5315.

Lu A, Frazier P, Kislev O (2018) Surge pricing moves uber's driver partners. *Available at SSRN 3180246* .

Lyft (2022) The driver's guide to pay. https://www.lyft.com/driver/pay.

Lyft (2023) Lyft's fees. https://help.lyft.com/hc/e/all/articles/115012927407-Lyft-s-fees.

Mansur R (2022) Zero commission, no surge pricing: Drife takes on ola, uber with blockchain tech. https://yourstory.com/the-decrypting-story/drife-decentralised-taxi-ride-hailing-ola-uber-blockchain.

Marshall A (2021) Gig workers gather their own data to check the algorithm's math. https://www.wired.com/story/gig-workers-gather-data-check-algorithm-math/.

Martin N (2019) Uber charges more if they think you're willing to pay more. https://www.forbes.com/sites/nicolemartin1/2019/03/30/uber-charges-more-if-they-think-youre-willing-to-pay-more/?sh=6fd151973654.

Mejia J, Parker C (2021) When transparency fails: Bias and financial incentives in ridesharing platforms. *Management Science* 67(1):166–184.

Mejia J, Urrea G, Pedraza-Martinez AJ (2019) Operational transparency on crowdfunding platforms: effect on donations for emergency response. *Production and Operations Management* 28(7):1773–1791.

Menegus B (2020) Shipt's 'effort-based' pay model decided a 1,400-item order was worth about $20. hhttps://gizmodo.com/shipts-effort-based-pay-model-decided-a-1-400-item-orde-1845180556.

MIT Media Lab (2020) Bargaining with the algorithm: pooling worker data to estimate gig economy worker pay. https://www.media.mit.edu/articles/bargaining-with-the-algorithm-shipt-shopper-pay/.

Möhlmann M, Henfridsson O (2019) What people hate about being managed by algorithms, according to a study of uber drivers. *Harvard Business Review* 30(August):1–7.

Möhlmann M, Zalmanson L, Henfridsson O, Gregory RW (2021) Algorithmic management of work on online labor platforms: When matching meets control. *MIS Quarterly* 45(4).

Newcomer E (2017) Uber starts charging what it thinks you're willing to pay. https://www.bloomberg.com/news/articles/2017-05-19/uber-s-future-may-rely-on-predicting-how-much-you-re-willing-to-pay#xj4y7vzkg.

O'Donovan C (2019) Delivery startups are using tips to fulfill pay promises, and customers are mad. https://www.buzzfeednews.com/article/carolineodonovan/delivery-startups-are-using-tips-to-fulfill-pay-promises.

Ola (2023) Commissions. https://ola.co.nz/commissions/.

Ola New Zealand (2022) Ola new zealand driver earnings and payments. https://ola.co.nz/driver/drivers-guidelines/ola-new-zealand-driver-earnings-and-payments/.

Ong HY, Freund D, Crapis D (2021) Driver positioning and incentive budgeting with an escrow mechanism for ride-sharing platforms. *INFORMS Journal on Applied Analytics* 51(5):373–390.

Özer Ö, Zheng Y (2016) Markdown or everyday low price? the role of behavioral motives. *Management Science* 62(2):326–346.

Özkan E, Ward AR (2020) Dynamic matching for real-time ride sharing. *Stochastic Systems* 10(1):29–70.

Prat A (2005) The wrong kind of transparency. *American economic review* 95(3):862–877.

Rahman HA (2021) The invisible cage: Workers' reactivity to opaque algorithmic evaluations. *Administrative Science Quarterly* 66(4):945–988.

Raval N, Dourish P (2016) Standing out from the crowd: Emotional labor, body labor, and temporal labor in ridesharing. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, 97–107.

Rose Dickey M (2020) Shipt shoppers are the latest gig workers to organize. https://techcrunch.com/2020/02/24/shipt-shoppers-are-the-latest-gig-workers-to-organize/.

Ryan RM, Deci EL (2000) Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology* 25(1):54–67.

Schieber J (2015) 99taxis raises "significant" new cash from tiger global. https://techcrunch.com/2015/02/02/99taxis-raises-significant-new-cash-from-tiger-global/.

Schuber C (2022) 'apps ramp up control to maximize profits': Gig workers speak out as seattle considers labor law. https://www.geekwire.com/2022/apps-ramp-up-control-to-maximize-profits-gig-workers-speak-out-as-seattle-considers-labor-law/.

Selyukh A (2019) At the mercy of an app: Workers feel the instacart squeeze. https://www.npr.org/2019/11/25/778546287/at-the-mercy-of-an-app-workers-feel-the-instacart-squeeze.

Shiptlist (2020) https://www.shiptlist.org/.

Siddiqui F (2021a) You may be paying more for uber, but drivers aren't getting their cut of the fare hike. https://www.washingtonpost.com/technology/2021/06/09/uber-lyft-drivers-price-hike/.

Siddiqui F (2021b) You may be paying more for uber, but drivers aren't getting their cut of the fare hike. https://www.washingtonpost.com/technology/2021/06/09/uber-lyft-drivers-price-hike/.

Silberling A (2021) Instacart shopper activists are going on strike. https://techcrunch.com/2021/10/15/instacart-shopper-activists-are-going-on-strike/.

Snyder C, Keppler S, Leider S (2022) Algorithm reliance under pressure: The effect of customer load on service workers. *Available at SSRN 4066823* .

Sun J, Zhang DJ, Hu H, Van Mieghem JA (2022) Predicting human discretion to adjust algorithmic prescription: A large-scale field experiment in warehouse operations. *Management Science* 68(2):846–865.

Taylor TA (2018) On-demand service platforms. *Manufacturing & Service Operations Management* 20(4):704–720.

Thaler RH (1988) Anomalies: The ultimatum game. *Journal of economic perspectives* 2(4):195–206.

Thaler RH (1999) Mental accounting matters. *Journal of Behavioral decision making* 12(3):183–206.

Toh A (2022) Gig workers think they work for themselves. they don't. https://www.sfchronicle.com/opinion/openforum/article/gig-workers-17509777.php.

Uber (2022) What is the upfront fare? https://help.uber.com/driving-and-delivering/article/what-is-the-upfront-fare?nodeId=bc83ed7e-6725-41de-afcb-72d263e5589f.

Uber Blog (2021) Upcoming changes to the driver app. https://www.uber.com/blog/california/upcoming-changes-to-the-driver-app/.

Uber ESG Report (2023) Environmental, social, and governance report. https://s23.q4cdn.com/407969754/files/doc_downloads/2023/04/Uber-2023-Environmental-Social-and-Governance-Report.pdf?uclick_id=3b0393ec-c06c-4a04-a761-7ecf7b9d8805.

Uber Help (2022) What is the upfront fare? https://help.uber.com/driving-and-delivering/article/what-is-the-upfront-fare?nodeId=bc83ed7e-6725-41de-afcb-72d263e5589f.

Uber Marketplace (2023) How can pricing serve riders and drivers? https://www.uber.com/us/en/marketplace/pricing/service-fee/.

Ullmann AA (1985) Data in search of a theory: A critical examination of the relationships among social performance, social disclosure, and economic performance of us firms. *Academy of management review* 10(3):540–557.

Vallas S, Schor JB (2020) What do platforms do? understanding the gig economy. *Annual Review of Sociology* 46(1):273–294.

Via (2022) Via's revenue based payments. https://drivewithvia.com/push/revenue-based-payments/.

Wagner P (2018) Ride-hailing apps surpass regular taxis in nyc. https://www.statista.com/chart/13480/ride-hailing-apps-surpass-regular-taxis-in-nyc/.

Wiener M, Cram W, Benlian A (2021) Algorithmic control and gig workers: a legitimacy perspective of uber drivers. *European Journal of Information Systems* 1–23.

Wood AJ, Graham M, Lehdonvirta V, Hjorth I (2019) Good gig, bad gig: autonomy and algorithmic control in the global gig economy. *Work, Employment and Society* 33(1):56–75.

Wu Y, Loch CH, Heyden LVd (2008) A model of fair process and its limits. *Manufacturing & Service Operations Management* 10(4):637–653.

Yan C, Zhu H, Korolko N, Woodard D (2020) Dynamic pricing and matching in ride-hailing platforms. *Naval Research Logistics (NRL)* 67(8):705–724.

Yang P, Iyer K, Frazier P (2019) Information design in spatial resource competition. *arXiv preprint arXiv:1909.12723* .

Yoon Y, Gürhan-Canli Z, Schwarz N (2006) The effect of corporate social responsibility (csr) activities on companies with bad reputations. *Journal of consumer psychology* 16(4):377–390.

Yufeng K (2022) Drivers to pay higher commission of 15https://www.straitstimes.com/singapore/transport/drivers-to-pay-higher-15-commission-to-gojek-from-feb-1.

Zeelenberg M (1999) Anticipated regret, expected feedback and behavioral decision making. *Journal of behavioral decision making* 12(2):93–106.

Zhang Y, Donohue K, Cui TH (2016) Contract preferences and performance for the loss-averse supplier: Buyback vs. revenue sharing. *Management Science* 62(6):1734–1754.

Zhou Y (2022) Uber is hiding customer payments from drivers. again. https://missionlocal.org/2022/11/uber-hiding-customer-payments-from-drivers/.

VITA

Swanand Kulkarni is a doctoral candidate in the Operations Management department in the Scheller College of Business at Georgia Institute of Technology. He earned a Master of Science degree in Economics and in Statistics from Georgia Institute of Technology. He holds a Bachelor of Technology degree in Metallurgical and Materials Engineering from Visvesvaraya National Institute of Technology.