Unraveling the Implications of Silent Labor Time (SLT) in the Gig Economy

Abstract

The gig economy has become integral to the global economy, driven by the labor flexibility it affords companies and the self-scheduling options available to workers. However, it also introduces an additional discretion for workers; they need to search for tasks during downtime, i.e., intervals when the platform does not assign them tasks. This period of uncompensated task-seeking, which we call "Silent Labor Time (SLT)," necessitates balancing effort between searching and executing tasks, impacting execution time. Our research aims to establish how the effort allocated during SLT affects workers' performance and earnings and identify factors that moderate this relationship. In food delivery, the distance drivers travel to find the next order, called "relocation distance," represents the effort allocated during SLT. Collaborating with a food delivery platform, we find that, on average, drivers relocate 2.6 km before each order, and a km increase in relocation distance reduces order allocation by 5.4%, order speed by 2.7%, and earnings by 14.8% in the subsequent hour. The primary reason for this decline is drivers allocating significant effort to searching for tasks during SLT, subsequently conserving energy when executing tasks. Relocations that are not towards familiar clusters and reduce supply-demand balance are most detrimental to workers' performance and earnings. Our findings suggest that relocation adversely affects drivers' earnings and operational performance in subsequent orders, ultimately impacting the platform's efficiency. We offer actionable insights by suggesting strategies for the management of effort allocation during SLT by different driver groups.

Keywords: Platforms, Gig Economy, Effort Allocation, Behavioral Operations, Food Delivery.

1. Introduction

Over the past decade, the gig economy has transformed the work landscape, introducing new levels of flexibility and opportunity while challenging established norms. It is currently valued at $455.2 billion[1] and is expected to reach $873 billion by 2028.[2] It has significantly impacted third-party logistics, especially in the last-mile, food, and grocery delivery. By 2027, with a global population of 8.33 billion,[3] 2.5 billion people will have food delivered to their homes.[4] Several factors contribute to this unprecedented growth, including growing consumer demand for convenience and speed,[5] company labor flexibility (Allon et al.

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[1]https://www.financialexecutives.org/FEI-Daily/September-2023/The-Gig-Economy-How-Financial-Executives-Can-Bette.aspx
[2]https://www.rapyd.net/blog/gig-economy-trends-2023/
[3]https://www.worldometers.info/world-population/world-population-projections/
[4]https://www.statista.com/outlook/dmo/online-food-delivery/worldwide#users
[5]https://ulaads.eu/the-on-demand-economy-and-its-impact-on-urban-logistics/

2023b), and worker self-scheduling capacity (Cachon et al. 2017). Despite this growth, the gig economy faces unique operational hurdles, notably in aligning supply and demand effectively. Traditional service system solutions often fall short in this business model, hindered by challenges like limited managerial control over gig workers' decisions and performance (Benjaafar and Hu 2020). Moreover, gig workers systematically devise their work strategies with substantial flexibility and autonomy,[6] influencing their decision-making processes and overall system efficiency.

Gig workers wield considerable influence across various sectors, such as logistics and food delivery, due to a pronounced reliance on their services. However, the prevailing notion that gig workers lack economic significance and are only interested in available work opportunities can lead to misconstruing their behavior.[7] It is essential to study their behavior to improve overall system efficiency. Various factors influence worker performance, such as discretion in selecting and organizing allocated tasks, facility layout (Meng et al. 2021), and commute between tasks (KC and Tushe 2021). However, the gig economy adds a novel dimension of discretion, where workers must not only choose but also actively search for tasks. This process requires a significant effort on the part of the workers. Thus, understanding the impact of this additional discretion on workers' productivity is crucial, particularly in the gig economy, characterized by unpredictable task locations and assignments.

Unlike traditional employment, where downtime is often a low activity or rest period, gig workers must search for tasks during downtime. We term this interval of uncompensated task-seeking "Silent Labor Time (SLT)," which requires gig workers to judiciously exert their efforts in search of the next task. In contrast to traditional employment, where firms must pay workers during downtime, SLT in the gig economy remains uncompensated. Consequently, companies prefer to have many idle workers available at any given moment to achieve quick response times, encouraging excess capacity and under-utilizing workers' time. A recent survey[8] of ride-hailing drivers indicates that almost 50% of their working hours are SLT. Additionally, platforms require workers to expend unpaid effort during SLT to meet dispersed demand while maintaining efficiency during execution time. Given that efforts are limited in quantum and inter-temporal allocation, this balancing act can lead to a trade-off between effort and time expended to search for and execute a task, impacting execution time performance. SLT is an important phenomenon to study due to its implications for the on-demand delivery platforms, which promise precise delivery times. SLT has also become a subject of debate among policymakers, as it remains uncompensated. Therefore, our research aims to establish the impact of effort allocated during SLT on subsequent performance.

[6] https://www.entrepreneur.com/starting-a-business/how-the-gig-economy-will-impact-the-future-of-work/458482
[7] https://www.ft.com/content/5a817da3-c55f-4b6f-8375-6c18db0406f2
[8] https://static1.squarespace.com/static/53ee4f0be4b015b9c3690d84/t/5effff2647a3f573481a187c/1593835306875/Parrott_Report_July22020.pdf#page58

In this study, we answer three important questions: a) What is the impact of effort allocated during SLT on workers' performance and earnings, and the mechanism behind it? b) What factors moderate this relationship? c) How does the impact of effort allocated during SLT vary among types of workers? We conduct our research in collaboration with a major Asian food delivery platform. SLT is a critical operational phase for both platforms and drivers in food delivery. Platforms rely on drivers to relocate during SLT to manage spatially asymmetric demands (Wang et al. 2023) and reduce customer wait times (Li et al. 2019). Conversely, drivers, burdened by lengthy unpaid SLT, relocate to find opportunities. Thus, we study how the distance drivers travel during SLT, i.e., relocation distance, affects their performance and earnings in the subsequent hour. To our knowledge, this study is the first to empirically analyze the impact of effort allocated during SLT in the gig economy, utilizing a large proprietary dataset.

Using instrumental variable regression, we establish that relocation distance negatively impacts drivers' performance and earnings. As an instrument, we employ the average relocation distance of the co-workers after delivering an order in the same customer area up to the previous day. We show that an increase in one km relocation distance results in a 5.4% decrease in the number of orders, a 2.7% reduction in speed, and a 14.8% drop in earnings in the following hour. We explain these findings by the psychological mechanism of effort allocation between searching for a task and executing it. We then identify the types of relocation that moderate the impact on performance and earnings. Relocations that enhance supply-demand balance, i.e., relocations to supply-shortage zones, which we categorize as imbalanced clusters, and relocations to familiar clusters alleviate the negative impact of effort allocation during SLT. Relocations that diminish supply-demand balance and are not towards familiar clusters are the most detrimental to performance and earnings. These results are substantiated through robustness tests using a binary treatment variable and various performance metrics.

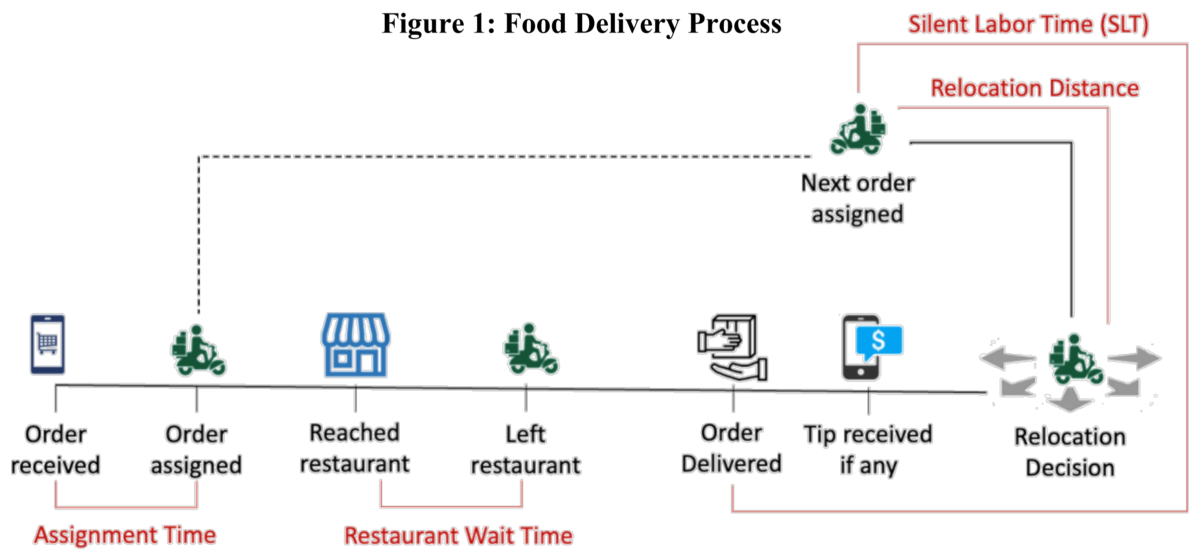
This study's findings have practical implications for workers and platforms in the gig economy sector. Workers can strategically make more informed decisions based on their objectives if they better understand the consequences of these decisions. For instance, relocating to a familiar cluster with a high supply-demand imbalance will help their performance and earnings. Similarly, by understanding workers' decisions, platforms can develop strategies that influence supply elasticity through network rebalancing, enhancing worker satisfaction and operational efficiency. One such strategy is to leverage cluster affinity (the tendency to relocate to a geographical cluster) of drivers to increase relocations that enhance the supply-demand balance. We explain that anchoring plays a crucial role in shaping cluster affinity, and platforms can manage it by nudging drivers that are more amenable to relocation only at the start of their workday.

2. Food Delivery Process

As illustrated in Figure 1, when a customer orders via the platform app, the proprietary algorithm assigns it to one of the drivers closest to the restaurant. The driver then drives to the restaurant to pick up the meal and has to wait there until the restaurant prepares it. Once the order is ready, the driver's next step is to navigate toward the customer's address for meal delivery.

The platform equips food delivery drivers with a smartphone application (app) to streamline the delivery process. This app provides access to order information, including the distance of the pick-up restaurant, the distance to the customer's location, and the value of the order. Refer to Figure A.1a in the online appendix[9] for screenshots of the app. Through this interface, drivers can either accept or decline incoming orders. Upon acceptance, the order specifics become visible within the app. Subsequently, after procuring the order from the designated restaurant, drivers must confirm the pick-up by selecting the 'Order picked up' option (Figure A.1b). This action triggers the display of navigational instructions to the customer's address. Upon arrival, drivers must indicate their location by selecting the 'Arrived at customer location' option (Figure A.1c).

Figure 1: Food Delivery Process



After completing a delivery, the driver faces a strategic decision regarding their subsequent action. They may either stay near the customer's location, anticipate another order, or decide to relocate. The period from the end of one delivery to the assignment of the next, which we term 'Silent Labor Time (SLT),' represents the driver's unpaid waiting time. Should they opt for relocation, 'relocation distance' refers to the distance traveled during SLT from the customer's location to the location of their next assignment. Drivers receive payment based on the distance between the restaurant and the customer for each delivery,

[9] Note: All tables, figures, and sections having a prefix "A." are available in online appendix (e-companion).

with the payment structure following a step function of distance. While specific details of the incentive function are confidential, we have access to the driver earnings data for each completed order.

Our collaborator does not provide any ETA to drivers to avoid rash driving and ensure safety. They also assign only a single order to drivers at a time. Although some food delivery platforms offer multiple, or 'stacked,' orders, they typically do so only when demand is high and there are insufficient riders.[10,11] However, there has been a surge in delivery drivers worldwide, resulting in many not receiving enough orders.[12,13] Moreover, most drivers do not prefer stacked orders, as these often lead to extra waiting time without sufficient compensation[14,15] and can result in dissatisfied customers.[16]

3. Related Literature

We contribute to two streams of literature in operations management: People Centric Operations (PCO) and the literature studying the gig economy. PCO is "the study of how people affect the performance of operational processes" (Roels and Staats 2021). Much of the existing PCO research focused on integrating worker or customer behavior into decision-making to optimize performance (Cho et al. 2019) and understanding the strategic behavior of customers (Gallino et al. 2022, Kabra et al. 2020). Only a few studies examined factors impacting workers' behavior, such as gamified training (Buell et al. 2022), process automation (Beer et al. 2024), and just-in-time scheduling (Kamalahmadi et al. 2021). A workstream within PCO has focused on identifying factors influencing worker productivity in allocated tasks. Meng et al. (2021) highlighted the understudied impact of facility layout on service workers, and KC and Tushe (2021) suggested that a longer commute between tasks affects productivity. Further, Meng et al. (2021) explained a marked divergence between service operations and manufacturing, noting that the former affords workers a degree of discretion in organizing their tasks. Researchers have explored how various aspects of work discretion, such as capacity allocation, processing time, task sequence, and speed-quality trade-offs, impact productivity (Ibanez et al. 2018). Similarly, KC et al. (2020) studied how individuals self-select tasks from pre-assigned tasks. Jeon et al. (2024) established how allowing shift choice can improve worker well-being and reduce turnover. Interestingly, in the gig economy, workers not only have the flexibility to choose tasks but also bear the additional effort of searching for the tasks during SLT and deciding whether to accept or

[10] https://riders.deliveroo.com.sg/en/tech-round-up-stacking-orders
[11] https://www.grab.com/sg/blog/public-policy/how-does-grab-match-trips-and-orders-to-driver-and-delivery-partners/
[12] https://www.aljazeera.com/economy/2023/9/8/thailands-food-delivery-drivers-see-wages-slump-as-platforms-cut-costs
[13] https://www.channelnewsasia.com/singapore/food-delivery-riders-earnings-accidents-study-protection-needs-3044001
[14] https://www.reddit.com/r/deliveroos/comments/ozeis2/hello_other_riders_are_stacked_orders_not_meant/
[15] https://www.channelnewsasia.com/cna-insider/decent-wages-income-gig-economy-food-delivery-riders-3371381
[16] https://consumergravity.com/can-doordash-pickup-multiple-orders/

decline these tasks. We study how the effort allocated during SLT impacts performance, especially in settings where SLT and the next task's location are uncertain and task assignment is not guaranteed, leveraging data from the food delivery process.

In the second stream, studying the gig economy, there has been limited research on understanding worker behavior (Donohue et al. 2020). Existing studies primarily focused on the impact of external factors on participation decisions (Liu et al. 2014). For instance, the effect of bonuses (Chen et al. 2022), average hourly wage (He et al. 2022), ratings, and penalties (Xu et al. 2023) on daily working hours. Some studies have also explored the impact of external factors on worker behavior and work quality. Examples include the effect of financial incentives on delivery acceptance time (Zhang et al. 2023) and restaurant density on delivery time (Zhang et al. 2023b), workers' response to wage cuts (Chen and Horton 2016), and the impact of a credible threat of monitoring on employee misconduct (Burbano and Chiles 2021). However, few papers studied the effects of gig workers' decisions on their performance and earnings, such as examining how income and time-targeting decisions affect work duration (Allon et al. 2023b). We focus on drivers' effort allocation decisions and their effect on performance.

Within the gig economy, drivers relocate during SLT to their next location after completing a task in sectors like ridesharing and food delivery. This relocation is vital for both platforms and drivers, addressing the operational challenge of the supply-demand imbalance (Feng et al. 2021). Platforms manage spatially asymmetric demands (Wang et al. 2023) and reduce customer wait times (Li et al. 2019) through driver relocation and optimizing order-driver matching algorithms (Zhao et al. 2024). Drivers, who face long unpaid idle times,[17,18] relocate to seek more work. Research across fields such as operations management (Hu et al. 2022), computer science (Jahanshahi et al. 2022), and transportation science (Ashkrof et al. 2020) has investigated driver relocation, proposing strategies for platforms to facilitate efficient relocation (Ma et al. 2019). Efficiency in this context refers to drivers being in the right place at the right time to meet consumer demands promptly (Guda and Subramanian 2019). Studies have examined strategies like surge pricing (Afèche et al. 2023, Hu et al. 2022) and information sharing (Guda and Subramanian 2019) for driver relocation but with contrary conclusions about their impact on driver behavior and earnings (Cachon et al. 2017, Jiang et al. 2021). Moreover, drivers often deviate from recommended relocations, leading to operational issues like supply-demand mismatches (Besbes et al. 2021) and extended delivery times (Gläser et al. 2021), affecting service quality.

Our research identifies critical research gaps in the existing literature on driver relocation. First, existing literature primarily focused on the challenges platforms face in efficient relocation (Besbes et al. 2021), overlooking the effects of relocation on workers' performance and assuming demand and incentives to be

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[17] https://vietcetera.com/en/always-on-the-go-a-day-in-the-life-of-a-food-delivery-rider
[18] https://cms.uitp.org/wp/wp-content/uploads/2020/11/Statistics-Brief-TAxi-Benchmarking_NOV2020-web.pdf

the only relocation motives (Allon et al. 2023a, Jiang et al. 2021). Second, while most studies focus on two-sided platforms like ride-hailing, the increasingly prevalent three-sided platforms, such as food delivery (Benjaafar and Hu 2020), which present more complexity due to hyperlocal matching and specific delivery conditions (Choudhary and Sen 2021), remain understudied. Moreover, strategies emphasized in ride-hailing studies, like surge pricing to benefit the platform (Cachon et al. 2017), often do not apply to food delivery owing to its smaller service radii (Zhou et al. 2023). Third, food delivery literature focuses on creating efficient delivery routes to minimize fuel consumption, reduce delivery time, and achieve high customer satisfaction.[19] However, the step preceding delivery (i.e., SLT), where drivers actively search for tasks and relocate to different locations, is often overlooked. The lack of granular data on drivers' relocation may be a reason for these gaps.

Therefore, understanding the impact of the effort allocated to relocate on workers' performance is essential to avoid suboptimal outcomes. While much research has been platform-centric (Besbes et al. 2021), often overlooking drivers' welfare, Allon et al. (2023a) is the only paper that examined relocation from the drivers' perspective. Using a structural model, the authors suggested that relocation improves driver performance and earnings. However, they assume that drivers make utility-maximizing relocation choices to maximize earnings, and the cost of relocation only includes the cost of fuel, the effort to relocate, and the opportunity cost of time. In summary, relocation has been studied analytically in the context of ride-hailing from the perspective of platforms. The literature lacks a comprehensive exploration of drivers' decision-making processes and the impact of these decisions on performance. Our paper addresses this critical gap by empirically studying the effects of relocation on drivers in a food delivery platform.

4. Theoretical Framework and Hypotheses Development

The existing literature has extensively studied the relationship between workload and productivity (Tan and Netessine 2014). For instance, research has examined the impact of workload on service times in patient transport services (KC and Terwiesch 2009) and the effect of fluctuations in nurse workload on absenteeism (Green et al. 2013). However, the concept of downtime has received less attention in operations management research. Brodsky and Amabile (2018) proposed the downtime and pacing theory, suggesting that workers who anticipate downtime after completing a task tend to work slower and take longer to finish it. They argue that the apparent cost of downtime is the monetary cost associated with firms paying workers during unproductive periods, leading workers to mask their downtime by slowing down. Nonetheless, they highlight that the impact of uncertain downtime remains unexplored. While some researchers have argued that rest breaks improve worker productivity as recovery during rest mitigates the negative impact of fatigue

[19] https://shipscience.com/optimizing-your-food-delivery-route-for-maximum-efficiency/

(Bechtold et al. 1984, Bechtold and Thompson 1993), this may not apply to gig workers, as they continue to exert effort in searching for their next task during downtime.

In summary, the existing literature on workload and downtime indicates that anticipated downtime tends to slow down workers unless used for resting and recovery. However, stark differences exist between the contexts studied in the extant literature and the gig platform setting. First, SLT in the gig economy is unpredictable, frequent, and uncertain. Second, gig workers receive no compensation from the platform during SLT, despite the incentives for both the platform and the drivers stemming from the effort allocated during SLT. Third, SLT is not an idle period of low activity during which workers can recover; instead, they have strong implicit incentives to exert effort during SLT to secure their next task and reduce the unpaid interval. Given these differences, the existing literature falls short of providing clear guidance on understanding the impact of effort allocation during SLT on workers' performance.

To theoretically examine this context, we leverage the Conservation of Resources (COR) theory introduced by Hobfoll (1989), which provides a framework for understanding how individuals act to acquire and preserve resources. For gig workers, the resource is the effort they invest in securing orders. The COR theory suggests that motivation intrinsically links to the conservation of resources, which is instrumental in achieving goals (Halbesleben et al. 2014). According to this theory, stress arises under three conditions: a threat of resource loss (i.e., anticipated effort in searching for a task), actual resource loss (i.e., actual effort in searching for a task), or lack of gain despite significant effort (i.e., not receiving a task despite substantial efforts in searching for a task) (Hobfoll et al. 2018). Given its theoretical relevance, we employ the COR theory to explain the negative impact of SLT on gig workers' performance and earnings.

While the COR theory has been extensively studied in psychology (Halbesleben and Bowler 2007), it has also been applied in organizational behavior research to explore the effects of feeling trusted on emotional exhaustion and performance (Baer et al. 2015), as well as the impact of organizational citizenship behavior on employee emotional exhaustion and job satisfaction (Koopman et al. 2016). Despite its broad applicability, researchers have not yet applied the COR theory to understand the operational behavior of gig workers. We leverage the COR theory as a theoretical lens for our research, which indicates that the effort allocated during SLT depletes the driver's resources.

We measure the effort allocated by the relocation distance traveled by the driver during SLT. The extended effort for longer relocations not only equates to immediate resource depletion but also signals an expected threat to resources in future endeavors. As elucidated by Hobfoll (2001) and Wang et al. (2022), upon perceiving such depletion and anticipated future threats, individuals tend to conserve their remaining resources, translating to diminished effort in the subsequent tasks. Therefore, we hypothesize that the greater the effort allocated during SLT, the less effort a driver will likely exert in the subsequent hour, diminishing their performance.

Hypothesis 1*: An increase in effort allocated during SLT is negatively associated with drivers' performance and earnings.*

The spatial locations of the workers are directly associated with the efficiency of matching demand with supply in gig delivery platforms. Guda and Subramanian (2019) emphasized the importance of generating balance in market zones with a worker shortage relative to demand. They noted that the number of idle workers in non-surge zones with excess workers is higher, and worker revenue is lower. Additionally, Bimpikis et al. (2019) highlighted that each additional driver is less valuable at locations with excess supply. Jiang et al. (2021) discussed that directing drivers to areas with greater demand augments platform revenues, boosting worker benefits and optimizing the match between supply and demand. In a parallel study, Besbes et al. (2021) argued that drivers relocating to a supply-overage zone would face reduced booking opportunities, adversely impacting their overall utility.

We define the type of relocation as balance-enhancing if the driver relocates to a supply-shortage zone; otherwise, we call it balance-diminishing. As discussed above, existing literature highlights that balance-enhancing relocation is not just an operational variable; it significantly influences a driver's financial trajectory and functional performance by enhancing their overall utility. Thus, balance-enhancing relocation will dimmish the signal of resource depletion, as argued above, leading to the following hypothesis:

Hypothesis 2*: Balance-enhancing relocation positively moderates the impact of relocation on drivers' performance and earnings.*

Behavioral biases impact an individual's decision and performance (Roels and Staats 2021). Understanding these biases is also essential from an implication or prescription perspective. Recent research on last-mile delivery highlights the significance of familiarity on driver performance. Specifically, Mao et al. (2022) posited that a driver's familiarity with the local area enhances the timeliness of deliveries. Dai et al. (2022) ascertained that gig workers tend to gravitate towards familiar delivery regions and stores after acquiring substantial experience. We interviewed drivers to understand whether familiarity impacts the food delivery drivers and gain insights into their workday. These interviews yielded valuable perspectives, highlighted by statements like:

- *"I come back to my area after delivering an order. If I get an order on the way, I take it; otherwise, I go back."*
- *"I have fixed my area and moved towards that area. Suppose I get an order on the way I deliver that; otherwise, I return to my area. I have a complete idea about all the buildings. For which building should I go to, the back entrance, front entrance, or the basement."*

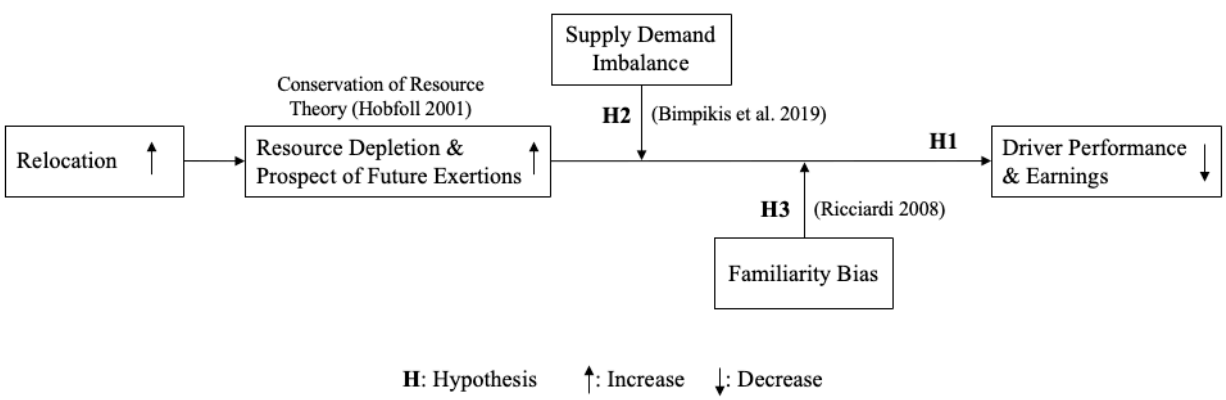
- *"I know for which towers customers will have to come down to collect the order, and it will take time for them to come. In such cases, I inform the customer 5-10 mins in advance that I am about to reach, which saves me time."*

Further, we lean on ambiguity aversion to comprehend the theoretical foundation of the impact of familiarity. Heath and Tversky (1991) suggested that individuals are more likely to engage in situations they perceive as familiar or where they feel knowledgeable or competent than unfamiliar ones. They broadly defined 'competence' to include skill, understanding, and knowledge. They argued that experience and familiarity strengthen this sense of competence. Furthermore, these authors noted that individuals, drawing on their accumulated life experiences, often deduce they perform better in situations they understand than in unfamiliar terrains. This predisposition persists even when the known and unknown situations have equal odds of success. This idea is in line with the Familiarity Bias theory. Ricciardi (2008) elaborated on this bias, defining "familiarity" as the level of knowledge or experience a person has with a specific task. He argued that individuals demonstrate greater risk tolerance in situations they recognize. Drawing on these insights, we hypothesize that relocation to a familiar cluster, i.e., *familiar relocation,* will induce the feeling of better utilization of resources, given that familiarity enhances the perception of competence and uncertainty tolerance. Thus, familiar relocations will alleviate the negative impact of resource depletion. Formally stated:

Hypothesis 3: *Familiar relocation positively moderates the impact of relocation on drivers' performance and earnings.*

Figure 2 provides a pictorial representation of the four hypotheses stated above.

Figure 2: Schematic Theoretical Framework



Note: An increase in effort allocated during SLT, measured by relocation distance, negatively impacts subsequent performance and earnings, an effect explained by the Conservation of Resources theory (H1). The supply-demand imbalance (H2) and familiarity bias (H3) moderate the magnitude of the impact of relocation distance.

5. Data and Model

We collaborate with an Asian food delivery platform to study the impact of relocation and understand the drivers' decision-making behavior. Our dataset spans one year (from May 2022 to April 2023) and includes data for all the drivers working for this platform in the Asian city. During this period, 6,028 drivers handled ~6.6 million orders received on the platform across the city. The platform categorizes drivers into four groups based on their work hours: Full-Time, Part-Time, Aspiring Full-Time, and Casual. Of these, 4,258 drivers work full-time in more than 90% of their work weeks, and we focus on these drivers for our main analysis. Additionally, to ensure the generalizability of our results, we excluded 345 drivers from the top and bottom 0.5% in terms of the number of orders completed. Thus, we have an initial sample of 3,913 drivers and ~5.4 million orders. Construction of the lagged regressors and control variables required us to drop observations; we excluded the last orders of the day and those assigned before finishing the previous order. Further, we drop some observations due to missing lat/long coordinates, yielding a final sample of ~3.5 million orders by 3,913 drivers. Note that our results continue to hold even when we include the top and bottom 0.5% of drivers.

Our dataset consists of two sets of data: *i) bookings* and *ii) captain info*. The *bookings* data provides granular details about each order, such as order time, assignment time, pickup time, delivery time, restaurant location, customer location, estimated distance, actual distance, payment method, order value, and the assigned driver's ID. We use this data to calculate variables like *relocation_distance* traveled by the driver and *order_speed* of the drivers. The anonymized *captain info* includes details about driver tenure, available hours, work segment, vehicle ownership status, and the number of orders completed every week. All the data we have received is aggregated and anonymized. To our knowledge, this is one of the most extensive datasets used in platform research to study driver behavior.

Using the city's administrative division data by municipality, we identify the divisions to which the customer and the restaurant belong. According to the government website, the city consists of geographical sub-areas. On the collaborating platform, restaurants span 146 sub-areas, and customers place orders from 396,942 locations across 185 sub-areas. Accordingly, we create variables for customer area, restaurant area, and familiarity with the customer area.

5.1. Definitions of Key Variables

We created an order-level panel where each observation corresponds to an order received by the platform. Table 1 describes our main variables, including our dependent variables: number of orders accepted by the driver in the hour post relocation (*num_orders.NH*), driver's average speed (in km/hr) during execution periods (when they are en route to collect an assigned order and the journey from the restaurant to the customer, excluding the wait time at the restaurant) in the hour after relocation (*order_speed.NH*), time (minutes) in the hour post relocation for which the driver has no assigned work

(*SLT.NH*), and amount (USD) earned by the driver in the hour post relocation (*earnings.NH*); treatment variable: geographical distance (km) traveled by the driver after the current order delivery and before she accepts the next order (*relocation_distance*); and control variables.

Table 1: Descriptive Statistics for Panel Data

Variable	*Description*	*Min*	*Mean (SD)*	*Max*
num_orders.NH	number of orders accepted by the driver in the hour post relocation	0	1.3 (0.7)	7.0
order_speed.NH	driver's average speed (in km/hr) during execution periods (when they are en route to collect an assigned order and the journey from the restaurant to the customer, excluding the wait time at the restaurant) in the hour after relocation.	0.3	20.6 (8.8)	46.4
SLT.NH	time (minutes) in the hour post relocation for which the driver has no assigned work	0	23.4 (11.7)	59.0
earnings.NH	amount (USD) earned by the driver in the hour post relocation	0	3.7 (2.8)	19.6
relocation_distance	geographical distance (km) travelled by the driver after current order delivery and before she accepts the next order	0	2.6 (2.3)	14.1
balance_enhancing	1 if the driver relocates to a supply shortage zone, 0 otherwise	0	0.3 (0.5)	1.0
familiar_relocation	1 if the driver relocates to a familiar restaurant cluster, 0 otherwise	0	0.6 (0.5)	1.0
tip	1 if the driver received tip for the order, 0 otherwise	0	0.1 (0.3)	1.0
rst_delay	time (minutes) between the driver reaching the restaurant for pick-up and leaving the restaurant with food	0.1	8.8 (6.8)	41.3
rst_delay.NH	sum of *rst_delay* for all orders assigned to the driver in one hour post relocation	0	11.6 (9.9)	80.0
familiarity	number of times driver has visited customer area before today	0	121.0 (168.0)	833.0
earnings	amount (USD) earned by the driver for the order	3.0	3.3 (0.2)	4.2
earnings_till_order	amount (USD) earned by the driver in the day before the order	0	14.6 (12.3)	134.0
perc.SLT_till_order	fraction of time for which driver was idle in the day before the order	0	33.9 (11.1)	86.0
pending_orders	number of orders pending at the restaurant from the same platform when driver arrived	1	1.7 (1.1)	6.0
orders_rst_area	number of orders received at the platform in the same order hour for same restaurant area	1.0	53.9 (49.5)	253.0
orders_cst_area	number of orders received at the platform in the same order hour for same customer area	1.0	44.5 (51.3)	313.0

We use a comprehensive set of controls that could potentially affect our dependent variables. Since fatigue can affect worker motivation (Duong et al. 2023), we should control for distance traveled and relocation distance till order. To account for income targeting and time-targeting, we should control for hours worked and earnings till order (Allon et al. 2023b). Since earnings till order correlate highly with distance traveled, relocation distance, and hours worked till order, we only use cumulative earnings till the current order (*earnings_till_order*) in the model. Monetary rewards such as tips can affect worker motivation (Castillo et al. 2022, Hidi 2016); therefore, we use *tips* as a control. In our interviews with the drivers, one of the drivers mentioned, "*I want to avoid restaurants where I have to wait longer, but I do not do it because I need to earn.*" Another driver echoed similar sentiments: "*If the restaurant delay is long, that slows me down and demotivates me.*" These excerpts suggest that waiting time, i.e., delay at the restaurant (*rst_delay*), can affect drivers' efficiency, and hence we control for it. As a proxy for market thickness, we use the number of orders received at the platform in the same order hour for the same restaurant area (*orders_rst_area*) and the same customer area (*orders_cst_area*) as the current order. Additionally, we account for variables such as the number of orders pending at the restaurant from the same platform when the driver arrived (*pending_orders*), the number of times the driver has visited the customer area before today (*familiarity*), and the fraction of time for which driver was idle in the day before the order (*perc.SLT_till_order*), which can potentially impact driver behavior.

5.2. Summary Statistics

Table 1 presents the descriptive statistics for our primary variables. On a typical day, a driver works for 10 hours, completes 10 orders, travels 2.4 km to reach a restaurant after receiving an assignment, covers 57 km between restaurants and customers, and relocates 22 km between deliveries during SLT. Figure A.2 provides the distribution of the daily distances a driver travels. The driver earns 32.5 USD from order deliveries and an additional 1.3 USD daily tips. To secure the following order, the driver has an average of 45 minutes of SLT and relocates 2.6 km. On a per-order basis, the driver travels 0.3 km to reach the restaurant post-assignment, waits for 9 minutes at the restaurant, covers 5.8 km to deliver the food from the restaurant to the customer, and earns 3.3 USD. Drivers receive payment based on the distance between the restaurant and the customer for each delivery, with the payment structure following a step function of distance. From the customer's perspective, the average cost of an order is 16.6 USD, and the waiting time from the moment of order placement to delivery is 34 minutes.

The pairwise correlations reported in Table A.1 reveal no multicollinearity issues in our data. We provide the distributions of all variables in Figure A.3.

5.3. Econometric Model & Identification

We identify the impact of relocation on driver efficiency using a fixed-effect linear regression model:

$$DV_{ikd} = \beta_1 treatment_{ikd} + \beta_2 controls_{ikd} + driver_i + date_d + peak\_hours_{ikd} + weekend_{id} + cst\_area_{ikd} + \varepsilon_{ikd} \quad (1)$$

In equation 1, the index k represents the order, i represents the driver, and d represents the date. The term DV_{ikd} denotes our dependent variables: *num_orders.NH, order_speed.NH, SLT.NH,* and *earnings.NH* and $treatment_{ikd}$ represents the treatment variable: *relocation_distance*. We employ the variables *num_orders.NH*, *order_speed.NH*, and *SLT.NH* to study the impact of *relocation_distance* on driver performance and *earnings.NH* to examine the effect on driver earnings, all measured in the hour immediately following the relocation (refer to Duong et al. 2023 for similar dependent variables).

5.3.1 Endogeneity

Relocation distance is likely endogenous due to the archival nature of our data, as the treatment is not randomly assigned. We conducted the Wu-Hausman test to assess the exogeneity of our treatment variable and rejected the null hypothesis, concluding that *relocation_distance* is indeed endogenous. There can be several threats to the identification of β_1, including unobserved heterogeneity, reverse causality, serial correlation, and omitted correlated variables (Antonakis et al. 2014). Drivers and deliveries may be heterogeneous in many ways. We employ a rich set of fixed effects to control for *unobserved heterogeneity* in addition to the controls explained in section 5.1. We use *driver* fixed effects to account for time-invariant individual-level heterogeneity and customer area (*cst_area*) for delivery area-specific heterogeneities, such as business districts or residential zones. *date* fixed effects control for factors such as seasonality (festive seasons, weather, etc.). Further, specific heterogeneities could be associated with the hour of the order and the day of the week. Therefore, we control for *peak_hours* and *weekend* fixed effects.

Performance depends on *relocation_distance*, but at the same time, performance can also impact the driver's actions. We introduce a temporal lag to address concerns related to *reverse causality*. We study the impact of relocation on the driver's efficiency in the next hour after delivering an order. One could argue that a driver's *relocation_distance* may exhibit serial correlation, or there could be serially correlated unobservables, such as the driver's effort. Using a similar approach as Duong et al. (2023), we verify that *serial correlation* in *relocation_distance* (0.04) is negligible after partialling out the effects of date, weekend, peak hours, and customer area.

Multiple sources of *omitted variable bias*, such as demand signals or customer experience in that area, can correlate with our dependent and treatment variables. We employ instrumental variable (IV) regressions using a two-stage least square (2SLS) model to address this issue, which we discuss next.

5.3.2 Instrumental Variables

Our treatment variable ($relocation\_distance_{ikd}$) represents the distance relocated after delivering an order *i*, in the customer area *k* (cst_area_k) on day *d*, respectively. We utilize the average *relocation distance* of the co-workers after delivering an order in the same customer area (cst_area_k) up to the previous day, $avg.co\_relocation_{ikd}$, as the IV for *relocation_distance*. Note that the customer area presents the administrative division of the city that contains the customer's address.

Let, $C_{kd}(i)$ be the set of co-workers of driver i who delivered orders in the customer area k on day d, excluding driver i. Let, $O_{kd}(i)$ be the set of orders delivered by $C_{kd}(i)$ in the customer area k on day d.

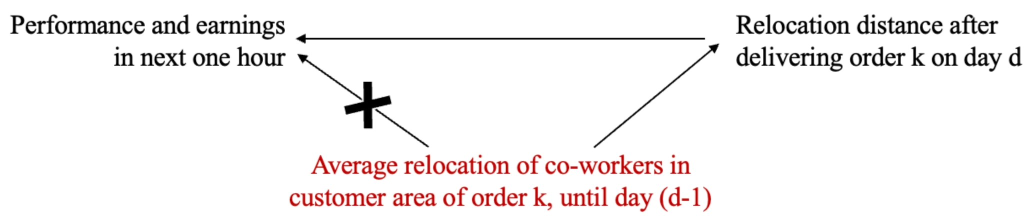
$|O_{kd}(i)|$ denotes the number of orders in the set $O_{kd}(i)$. We then define the variable $avg.co\_relocation_{ikd}$ (mean = 2.2, sd = 0.82) as follows:

$$avg.co\_relocation_{ikd} = \frac{total\ relocation\ of\ the\ co-workers\ after\ delivering\ in\ customer\ area\ k\ till\ date\ d-1}{total\ number\ of\ orders\ delivered\ by\ co-drivers\ in\ customer\ area\ k\ till\ date\ d-1}$$

$$= \frac{1}{\sum_{j=1}^{d-1}|O_{kj}(i)|} \sum_{j=1}^{d-1} \sum_{k' \in O_{kj}(i)} \sum_{i' \in C_{kj}(i)} relocation\_distance_{i'k'j} \tag{2}$$

As illustrated in Figure 3, we use $avg.co\_relocation_{ikd}$ as an IV for the driver's *relocation distance* and estimate equation (1) using the 2SLS method to identify the impact of relocation on drivers' performance and earnings.

Figure 3: Average Relocation of Coworkers as an Instrumental Variable



A valid IV must satisfy three conditions. First, the *relevance condition* requires that the IV correlates with the endogenous variable, *relocation_distance.* Peer attributes, commonly used as IVs in existing literature (Chan et al. 2021, Xu et al. 2023), play a significant role in our context. The conditions in their operating *customer area* likely influence the focal worker's *relocation distance*. The relevance condition is satisfied given that co-workers and the focal worker encounter similar circumstances, including demand patterns, traffic, parking availability, and customer behavior in the same customer area. This shared environment suggests that the co-workers' average *relocation distance* reliably reflects the factors affecting the focal worker, thereby *validating the relevance condition*. Allon et al. (2023a) also suggest that the delivery location is an essential predictor of driver relocation decisions. Note that we have customer area fixed effects, as mentioned in equation (1). However, fixed effects will only account for time-invariant area-specific heterogeneities. Our IV captures the time-variant experience, such as customer order assignment dynamics and the behavior of the co-workers in an area.

Second, the *exclusion restriction* necessitates that the IV be uncorrelated with the error term and influence the dependent variable only through the endogenous variable (Wooldridge 2002). In our case, we meet the exclusion restriction criterion because the *relocation distance* by co-workers on previous days does not impact the focal driver's performance and earnings for orders delivered after relocation today. One may argue that the *relocation distance* of co-workers might affect the customer's behavior in an area. However, even though we observe long *relocation distances* in the data, the total number of daily orders is almost consistent, i.e., *relocation distance* in an area does not significantly perturbate the system dynamics.

In simpler terms, co-workers' prior experiences and activities in the customer area do not directly affect the focal worker's performance during today's tasks. Consequently, the IV primarily predicts the independent variable without directly affecting the dependent variable, thus *satisfying the exclusion restriction criterion*.

Third, the IV should be *strong* enough to provide unbiased estimates (Stock and Yogo 2005). Our IV satisfies the relevance and strength conditions, as confirmed by the first stage of 2SLS: $avg.co\_relocation$ coefficient = 0.46 ($p \ll 0.01$) and F-stat = 705.4.

Further, addressing the inherent biases commonly found in peer effects contexts is also essential. Studying peer effects presents challenges, including *reverse causality*, *correlated unobservables*, and *selection bias* (refer to Bollinger and Gillingham 2012, Bramoullé et al. 2009, Manski 1993). We tackle *reverse causality* by using lagged relocation of co-workers (Bollinger et al. 2020, Ghose and Han 2011) and account for *correlated unobservables* through a comprehensive set of fixed effects (Hanushek et al. 2003). *Selection bias* is less pertinent in our context, as drivers are generally hesitant to reject or cancel orders due to the limited number of opportunities available. On average, out of the 10 hours the drivers work, they have an SLT of 4.9 hours and, consequently, only on 0.18% of the days do drivers reject any order.

A potential challenge in our identification strategy is the presence of unobserved factors that correlate with the average relocation of co-workers and the earnings of the focal worker – called the instrument ignorability assumption, which requires that no potential confounding factors directly affect the IV and the dependent variable simultaneously (Angrist et al. 1996). An example could be limited accessibility in a customer area, which might affect the earnings of both the focal worker and their co-workers in the hour following relocation from that area. To account for these unobservable factors, we control for the average performance and earnings of the co-workers in the next hour after their deliveries in the same customer area. Bobroske et al. (2022) and Freeman et al. (2021) use a similar approach to address instrument ignorability. The robustness of our findings, incorporating this additional control, is further detailed in section 8.

6. Results

In this section, we first estimate the impact of the effort allocated during SLT, i.e., relocation distance, on driver performance and earnings. Then, we study two types of relocation – balance-enhancing and familiar relocations and how these types moderate the impact.

6.1. Impact of Relocation Effort on Drivers' Performance

One or more of the following reasons may explain the decrease in drivers' performance: a) a decrease in the number of orders assigned, possibly due to slower speeds or a supply overage; b) drivers working slower and taking longer to complete assigned orders; c) longer SLT, either to conserve/regenerate energy or due to relocation to a supply overage zone; d) drivers not working at all in the following hour. To establish that effort allocation during SLT causes performance to decline, we analyze the impact of relocation on the number of orders assigned, speed, and SLT in the next hour. We analyze the types of relocation in Sections 6.2 and 6.3. For point d), we conduct a robustness analysis using a sub-sample of relocations where drivers completed at least one order in the next hour, as detailed in Section 8.

Table 2: Impact of Relocation on Performance and Earnings

	num_orders.NH	*order_speed.NH*	*SLT.NH*	*earnings.NH*
	(1)	(2)	(3)	(4)
relocation_distance	-0.070***	-0.554**	-0.181	-0.546***
	(0.016)	(0.278)	(0.329)	(0.084)
tip	0.007***	0.020	-0.076***	0.033***
	(0.001)	(0.017)	(0.021)	(0.005)
rst_delay	-0.003***	0.009***	0.022***	-0.010***
	(0.000)	(0.001)	(0.001)	(0.000)
rst_delay.NH	0.026***	0.043***	-0.653***	0.066***
	(0.000)	(0.001)	(0.002)	(0.000)
earnings	0.145***	2.059***	-0.296	1.038***
	(0.040)	(0.712)	(0.839)	(0.216)
earnings_till_order	-0.001***	0.037***	0.011***	0.020***
	(0.000)	(0.002)	(0.002)	(0.000)
familiarity	0.000**	-0.002**	0.001	-0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
pending_orders	0.001	-0.031***	0.012	0.026***
	(0.001)	(0.010)	(0.010)	(0.003)
orders_cst_area	0.000***	-0.005***	0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
orders_rst_area	0.000***	0.002***	-0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
perc.SLT_till_order	-0.001***	0.008***	0.007***	-0.001***
	(0.000)	(0.001)	(0.002)	(0.000)
adj-R^2	0.182	0.192	0.329	0.148
N	3,561,341	3,358,528	2,774,289	3,561,341

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

We present our 2SLS estimates of equation (1) in Table 2.[20] Table A.2 provides the OLS estimates, and Table A.3 details the first stage estimates of Column 1. Column 1 of Table 2 reveals that an increase in *relocation_distance* significantly diminishes the number of orders assigned in the subsequent hour (-0.070,

[20] We only calculate order_speed.NH when there is at least one order in the next one hour and SLT.NH when there are at least two more orders after focal SLT in the remaining day

p<0.01). To illustrate, a one-kilometer increment in *relocation_distance* equates to a 5.4% (0.070/1.3) reduction in the subsequent hour's order allocation. One could argue that per-order payment structures and an oversupply of drivers on the platform mitigate the impact of this reduction, but broader regulatory trends warrant attention. Globally, legislative shifts increasingly favor enhanced working conditions for gig workers, encompassing paid leave and health insurance benefits.[21] Operational performance becomes paramount, with impending regulations likely to prompt platforms to refine staffing strategies to curb overhead expenses. In this context, maximizing the number of orders fulfilled per unit of time by drivers instead of distributing a consistent order volume across a larger driver pool will be critical for platform sustainability and efficiency.

We measured the driver's speed during the next hour when they were working on an order. As shown in Column 2, a one-kilometer increase in *relocation_distance* leads to a decrease in speed by 0.554 km/hr in the next hour, equivalent to a 2.7% reduction (0.554/20.6). Given the platforms' emphasis on delivery speed, a decrease in delivery speed[22] might not only affect drivers' performance but could also impact customer satisfaction and overall service quality. In Column 3, we observe that relocation does not significantly impact SLT in the next hour. Column 4 shows that an increase in *relocation_distance* negatively impacts earnings in the next hour. Specifically, a one-kilometer increase in *relocation_distance* results in a 0.546 USD decrease in earnings for the next hour, equivalent to a 14.8% reduction (0.546/3.7). Overall, our results indicate that an increase in *relocation_distance* leads to drivers exerting less effort in the subsequent hour, thereby diminishing their performance (number of orders assigned: -0.070, *p<0.01;* speed: -0.554, *p<0.05*) and earnings (-0.546, p<0.01), which supports *Hypothesis 1*.

Since it is not feasible to distinctly analyze driver actions during SLT – whether they are relocating or resting – we also conduct a robustness analysis. This analysis aims to understand the impact of relocation on earnings per unit of busy time in the next hour. As detailed in Section 8, our results are consistent, validating our proposed mechanism of drivers conserving resources, leading to a decline in performance and reduced earnings.

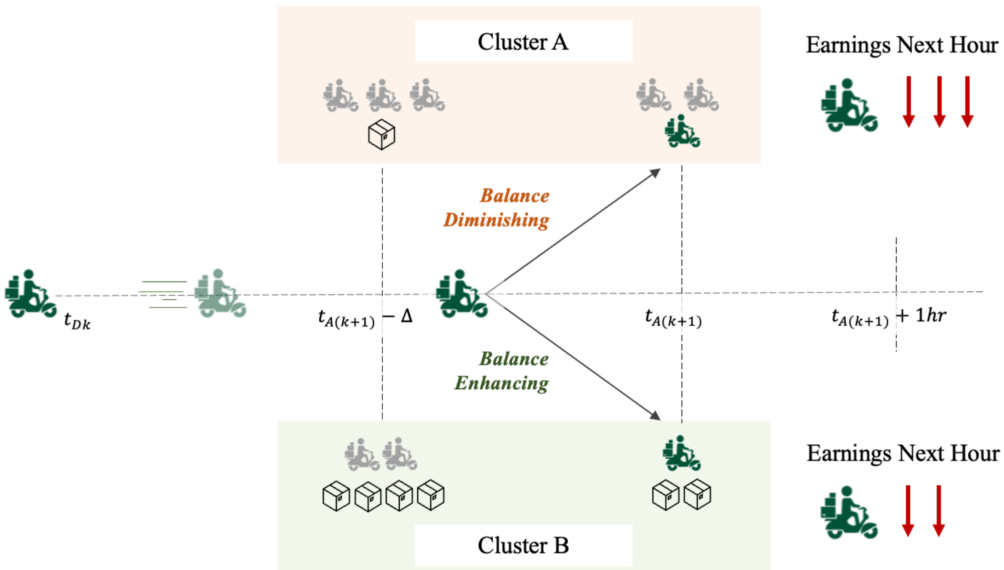
6.2. Balance Enhancing Relocation

Identifying whether drivers are relocating to a zone with a supply shortage or overage is essential to manage relocations and improve the supply-demand balance. Section 4 explains how drivers in high-demand areas contribute more significantly to platform revenues and their own benefits than those in supply overage areas where booking opportunities and driver utility may diminish. Achieving the right balance in

[21] https://www.straitstimes.com/asia/se-asia/countries-around-the-world-advancing-benefits-and-protections-for-gig-workers
[22] We strictly and actively discourage breaking speed limits. All these analyses are within speed limit. Also, slowing down within speed limit is not good for driver safety.

supply and demand enhances worker and platform benefits and meets broader needs by efficiently serving customers. Even though workers do not have specific information about the balance, they have reasonable estimates based on their experience. Due to the lack of precise location tracking for each driver, we use a proxy to assess the supply-demand imbalance.

Figure 4: Type of Relocation – Balance Enhancing vs Balance Diminishing



We only observe where a driver gets their next order, and we classify types of relocation accordingly. First, we cluster restaurants within a 270-meter radius. We selected this radius because, on average, drivers are 270 meters away from a restaurant at the time of order assignment. We propose that if supply is well balanced in a cluster, each order received should ideally be assigned to a driver within the median assignment time, denoted as an Δ. If at any given time t, there are orders received before $(t - \Delta)$ still pending assignment, we consider the cluster imbalanced; otherwise, we classify it as balanced. To quantify the type of relocation, we define relocation as *balance_enhancing* if, after delivering order k, the driver relocates to a cluster s that is imbalanced. Figure 4 visually illustrates the concept of the nature of relocation. Formally, we express this as:

$$balance\_enhancing_{ks} = \begin{cases} 1, & pending\_assignment_{t_{A(k+1)}s} > 0; \\ 0, & otherwise \end{cases}$$

$t_{A(k+1)}$: time when order $(\mathrm{k} + 1)$ is assigned to the driver in restaurant cluster s after relocation;

Δ: median assignment time for the platform across the city over one year;

$pending\_assignment_{ts}$: orders received in cluster s before $(t - \Delta)$ and remain unassigned at t

To assess the impact of the type of relocation on driver performance and earnings, we run an interaction model, as shown in Table 3. Since relocation does not significantly affect SLT in the next hour, we do not include it in the interaction analysis. Columns 1 and 2 show that *balance_enhancing* relocation alleviates the impact of relocation on driver performance. *Balance_enhancing* relocation reduces drivers' number of orders by 4.2% ((-0.073+0.018)/1.3) and speed by 1.7% ((-0.608+0.259)/20.6) in the next hour, compared to a 5.6% (-0.073/1.3) and 3.0% (-0.608/20.6) reduction, respectively, for *balance_diminishing* relocation. Column 3 indicates that *balance_enhancing* relocation also benefits drivers' earnings, mitigating the adverse effects of relocation by 2.5%. Specifically, it reduces drivers' earnings in the next hour by 12.8% ((-0.567+0.095)/3.7), compared to a 15.3% reduction (-0.567/3.7) for *balance_diminishing* relocation. Overall, drivers relocating to an imbalanced cluster experience improved opportunities and earnings, which benefit them. These relocations also enhance the driver performance and the match between supply and demand, helping the platform and increasing overall system utility. These results support our *Hypothesis 2,* which is that the *balance enhancing* relocation alleviates the negative impact of relocation on drivers' performance and earnings.

Table 3: Impact of Nature of Relocation on Driver Efficiency

	num_orders.NH	*order_speed.NH*	*earnings.NH*
	(1)	(2)	(3)
relocation_distance	-0.073***	-0.608**	-0.567***
	(0.017)	(0.302)	(0.091)
relocation_distance × *balance_enhancing*	0.018***	0.259***	0.095***
	(0.005)	(0.079)	(0.025)
balance_enhancing	0.021**	0.019	-0.035
	(0.010)	(0.172)	(0.056)
adj-R^2	0.186	0.194	0.149
N	3,561,341	3,358,528	3,561,341

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

6.3. Location Familiarity

Platforms require drivers to relocate to address spatially asymmetric demand. It is essential to understand how familiarity with the area impacts the outcome of relocations to optimize relocations for the system. Our interviews with drivers suggest that familiarity with the restaurant cluster significantly influences their efficiency. Consistent with the findings of the literature, individuals prefer engaging in familiar environments where they feel more knowledgeable and competent than unfamiliar ones (as elaborated in Section 4). This preference for familiar areas is evident in drivers' interview responses, where they often refer to certain restaurant zones as "my area," underscoring their affinity and detailed knowledge of these specific locations.

We create the *familiar_relocation* variable to quantify this behavior of drivers. We calculate V_c as the number of visits by the driver to cluster c until the day $(d-1)$ within a rolling window of the last 30 days. This dynamic estimation accounts for the evolving nature of familiarity with changes in exposure and experience. We only observe where drivers get their next order and quantify *familiar_relocation* accordingly. A cluster c is classified as *familiar* if $V_c > (median\ of\ V_{c'})$, where c' represents the set of clusters visited by the driver in the last 30 days until day $(d-1)$. We exclude each driver's first 30 days of data for more robust calculations. A relocation is defined as *familiar_relocation* if, after delivering order k, the driver relocates to a cluster s, which is a *familiar* cluster. Formally:

$$familiar\_relocation_{ks} = \begin{cases} 1, & V_s > (median\ of\ V_{c'}); \\ 0, & otherwise \end{cases}$$

Table 4: Impact of Familiar Relocation on Driver Efficiency

	num_orders.NH	*order_speed.NH*	*earnings.NH*
	(1)	(2)	(3)
relocation_distance	-0.078***	-1.354**	-0.642***
	(0.026)	(0.561)	(0.142)
relocation_distance × *familiar_relocation*	0.011***	0.135**	0.088***
	(0.003)	(0.058)	(0.016)
familiar_relocation	0.046***	1.106***	-0.116***
	(0.003)	(0.100)	(0.017)
adj-R^2	0.187	0.140	0.135
N	3,101,925	2,925,297	3,101,925

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

We study the effects of *familiar_relocation* on drivers' performance and earnings, with our results detailed in Table 4. Column 1 indicates that relocating to familiar clusters improves the number of orders assigned in the next hour. *familiar_relocation* reduces drivers' orders by 5.2% ((-0.078+0.011)/1.3) in the next hour, compared to a 6.0% (-0.078/1.3) reduction for *non familiar_relocation*. In Column 2, we observe that *familiar_relocation* reduces the impact of relocation on speed. *familiar_relocation* results in a 5.9% ((-1.354+0.135)/20.6) decrease in speed for the following hour, as opposed to a 6.6% (-1.354/20.6) decrease for *non familiar_relocation*. Column 3 indicates that relocating to familiar clusters mitigates the negative effect of relocation on a driver's earnings by 2.4%. Specifically, a one-kilometer increase in *familiar_relocation* results in a 15.0% ((-0.642+0.088)/3.7) decrease in earnings for the following hour, as opposed to a 17.4% (-0.642/3.7) decrease for *non familiar_relocation*. In summary, our findings indicate that drivers benefit from relocating to familiar areas, thus supporting our *Hypothesis 3* that *familiar_relocation* alleviates the impact of relocation on drivers' performance and earnings.

6.4. Balance-Enhancing and Familiar Relocations

We have discussed the two types of relocation – *balance enhancing* and *familiar relocations* – as distinct categories, yet these two are not mutually exclusive. It is crucial to determine whether *balance enhancing* relocations, which improve supply-demand matching, are also the type of relocation preferred by drivers, i.e., *familiar relocation*. Additionally, we consider whether drivers enhance system balance and overall system utility while relocating to familiar areas. Table 5 presents the composition of different types of relocations and summarizes the results of our three-way interaction model used to estimate the impact on the number of orders (*num_orders.NH*) and earnings (*earnings.NH*), given that the two types of relocations significantly impact the two dependent variables.

Although *balance enhancing* relocations result in 12% higher earnings and 6% more orders for drivers (with average earnings of 4.1 USD and 1.6 orders in *balance enhancing* relocations compared to 3.6 USD and 1.5 orders in *balance diminishing* ones) and help mitigate the adverse effects of relocation to some extent, they constitute only 29.1% of all relocations. However, most relocations, 60.8%, are *familiar relocations*, with a notable 70% of *balance enhancing* relocations also falling into this category. These findings underscore the strong preference of drivers to relocate to familiar clusters, given the positive impact of familiar relocation on their efficiency.

Table 5: Balance Enhancing and Familiar Relocation

	Familiar Relocation	*Non-Familiar Relocation*
Balance Enhancing	% Relocation: 21.1% Avg. Relocation Distance: 2.70 km Avg. num_orders.NH: 1.65 Avg. earnings.NH: 4.16 USD Impact on num_orders.NH: -**4.4%** Impact on earnings.NH: **-13.4%**	% Relocation: 8% Avg. Relocation Distance: 2.24 km Avg. num_orders.NH: 1.53 Avg. earnings.NH: 3.98 USD Impact on num_orders.NH: -**5.5%** Impact on earnings.NH: **-16.2%**
Balance Diminishing	% Relocation: 39.7% Avg. Relocation Distance: 2.69 km Avg. num_orders.NH: 1.54 Avg. earnings.NH: 3.64 USD Impact on num_orders.NH: **-5.8%** Impact on earnings.NH: **-16.3%**	% Relocation: 31.2% Avg. Relocation Distance: 2.51 km Avg. num_orders.NH: 1.44 Avg. earnings.NH: 3.54 USD Impact on num_orders.NH: -**6.4%** Impact on earnings.NH: -**18.2%**

Drivers often travel longer distances for *familiar relocation*, even though *balance enhancing* relocations could yield higher performance and hourly earnings. We attribute this tendency to risk aversion and familiarity bias. In summary, relocations that are neither *familiar relocation* nor *balance enhancing* are the most detrimental to performance (a 6.4% reduction in the number of orders) and earnings (an 18.2% decrease). In comparison, those that are both *balance enhancing* and *familiar relocation* have the least negative impact (a decline of 4.4% in the number of orders and 13.4% in earnings). These findings suggest that platforms could improve operational performance and driver earnings by understanding the factors influencing drivers' relocation decisions.

So far, our analysis has focused on the impact of *relocation distance* at the order level. We have established that relocation negatively impacts driver performance and earnings, which understanding the type of relocation can alleviate. We have also discussed that relocation is crucial for platforms to meet dispersed demand and for drivers to seek tasks. Therefore, it is neither feasible nor advisable to prevent drivers from relocating. The question is, can we improve relocation for drivers' performance and earnings? Categorizing drivers based on their relocation behavior yields interesting insights about how strategic relocations can have a long-term impact, a topic we explore next.

7. Impact of Strategic Relocations by Drivers

We identify drivers with tendencies to travel longer relocation distances and a preference for *familiar relocation*. Data is aggregated at the driver-day level to categorize drivers into four groups. We calculate the average relocation distance traveled per day by a driver and classify drivers as *HR* (*high relocators*) if their average relocation distance per day worked exceeds the median; otherwise, they are termed *LR* (*low relocators*). Similarly, we calculate the fraction of relocations that were *familiar_relocation* out of the total orders delivered. We classified drivers as *FR* (*familiar relocators*) if this fraction exceeds the median; otherwise, we categorized them as *NFR* (*non-familiar relocators*).

Table 6 presents the composition of different types of drivers and critical day-level summary statistics for each category. It is crucial for drivers to optimize their output for the total hours worked and effort allocated during SLT. Therefore, we want to understand driver performance for each hour worked and every kilometer relocated. *LR*-FR completes 39.0% more orders and earns 39.9% more than HR-FR, supporting our *Hypothesis 1* that relocation hurts efficiency. *HR*-FR completes 10.8% more orders and earns 9.5% more than HR-NFR, further supporting our *Hypothesis 3* that familiar relocations are more efficient for the drivers. Further, LR-FR completes 54.1% more orders and earns 53.2% more than HR-NFR, suggesting that the LR-FR is the most efficient. These findings indicate that the strategy for relocation can significantly impact drivers' performance and earnings.

The platform needs to manage relocations to optimize drivers' performance. It can encourage HR-NFR to relocate towards imbalanced clusters, as they are more amenable to relocation and flexible due to their lack of attachment to specific areas. Two important groups, *HR-FR* and *LR-NFR*, could become more efficient by strategically managing their cluster affinity. *LR-FR* is the most efficient and warrants nurturing. These results highlight the importance of platforms better understanding and managing driver relocations. The discussion section below presents several strategies to manage relocation and cluster affinity.

Table 6: High Relocators and Familiar Relocators

	Familiar Relocators (FR)	*Non-Familiar Relocators (NFR)*
High Relocators (HR)	% Drivers: 35.5% SLT between orders: 35 mins Relocation: 21.8 km Hours worked: 10.6 Num of orders per hour per km relocated: $\mathbf{4.1}\times10^{-2}$ Earnings per hour per km relocated: $\mathbf{13.8}\times10^{-2}$ USD	% Drivers: 14.6% SLT between orders: 40 mins Relocation: 19.8 km Hours worked: 10.2 Num of orders per hour per km relocated: $\mathbf{3.7}\times10^{-2}$ Earnings per hour per km relocated: $\mathbf{12.6}\times10^{-2}$ USD
Low Relocators (LR)	% Drivers: 14.4% SLT between orders: 39 mins Relocation: 13.5 km Hours worked: 9.7 Num of orders per hour per km relocated: $\mathbf{5.7}\times10^{-2}$ Earnings per hour per km relocated: $\mathbf{19.3}\times10^{-2}$ USD	% Drivers: 35.5% SLT between orders: 42 mins Relocation: 11.6 km Hours worked: 8.8 Num of orders per hour per km relocated: $\mathbf{5.3}\times10^{-2}$ Earnings per hour per km relocated: $\mathbf{19.9}\times10^{-2}$ USD

8. Robustness

We conduct several robustness tests to establish the rigor of our results. We use an alternative treatment variable, *is_relocated*, a binary variable equal to 1 if the driver relocated at least 1 km before the assignment of the following order and 0 otherwise. Based on the literature, we used the threshold of 1 km for our primary treatment variable (Allon et al. 2023a). Table A.4 validates the directional robustness of our results.

We also employed alternative dependent variables to quantify drivers' earnings and performance. Specifically, we used earnings per hour, order speed, and the number of orders assigned per hour on the remaining day after relocation. As detailed in Table A.5, our results remain robust.

One could postulate that our results might be influenced by the drivers not working the following hour. To ascertain the robustness of our results, we conducted a sub-sample analysis of relocations where drivers completed at least one order in the next hour. All our results remain consistent, as presented in Table A.6.

We acknowledge that it is not feasible to distinctly analyze driver actions during SLT, whether relocating or resting. Therefore, we conduct an additional analysis to understand the impact of relocation on performance and earnings per unit of time during the busy period in the next hour. Table A.7 validates the directional robustness of our results.

To test the robustness of our instrumental variable, we add a control for the average performance and earnings of the co-workers in the next hour after their deliveries in the same customer area. As explained by Bobroske et al. (2022) and Freeman et al. (2021), this approach mitigates concerns regarding unobserved factors influencing both the dependent variable and the IV, also known as instrument ignorability (Angrist et al. 1996). The results remain robust, reinforcing our IV's validity, as shown in Table A.8.

Ultimately, we conduct a robustness analysis with more granular fixed effects. We use the hour the order was received, which we call *order_hour*, fixed effects instead of *peak_hours*. As presented in Table A.9, our results remain consistent.

9. Discussion and Conclusion

The gig economy heavily relies on workers' discretion to search for tasks, which demands significant time and effort and involves decisions to accept or decline opportunities. Additionally, workers in the gig economy do not feel compelled to address supply-demand mismatches. This dynamics necessitates that platforms comprehend the impact of their workers' effort allocation decisions during SLT to optimize the benefits of the gig economy's labor flexibility and minimize suboptimal outcomes.

Our study reveals the significant negative impact of effort allocated during SLT on driver performance and earnings. The primary reason for this decline in performance is the resources expended by drivers during SLT to search for the next task and then try to conserve their energy in subsequent task execution. In food delivery, relocation distance is the effort drivers allocate to search for the next order during SLT. In collaboration with a food delivery platform, our findings show that an additional kilometer of relocation decreases a driver's order assignments by 5.4%, speed by 2.7%, and earnings by 14.8% in the subsequent hour. This equates to an annual loss of around 1500 USD for a driver working 26 days a month, a significant amount for a blue-collar worker.

These findings contrast with Allon et al. (2023a), which suggests that relocation improves driver performance and earnings based on their structural model estimation. The authors have a small dataset (10% of the dataset we use), and in their initial OLS estimation, they control only the time of day and the amount of time spent working with fixed effects for workers' locations. In contrast, we employ a 2SLS estimation strategy on a much larger dataset with a rich set of controls and fixed effects. Further, the structural model in Allon et al. (2023a) assumes that drivers make utility-maximizing relocation choices to maximize earnings, and the cost of relocation only includes the cost of fuel, the effort to relocate, and the opportunity cost of time. However, as evident from our analysis, the relocation decision is affected by many other factors, such as SLT during the day, familiarity with customer area, time-targeting, income-targeting, and monetary rewards that we control. Further, we establish that supply-demand imbalance and familiarity with the restaurant (pick-up in the ride-hailing context) area influence the impact of relocation on performance and earnings.

Existing literature often simplifies relocation decisions to be influenced only by demand and financial incentives. However, we observe a significant influence of types of relocations in moderating its impact. Although platforms depend on driver relocations to address uneven demand across locations, not all relocations prove beneficial. Ideally, from the platform's perspective, relocations to supply shortage zones, termed *balance enhancing* relocations, are preferable. Even though *balance enhancing* relocations can lead to 12% higher earnings than *balance diminishing* relocations and help mitigate the adverse effects, only about 29.1% of all relocations fall into this category. Further, 60.8% of relocations are *familiar relocation,* which significantly alleviates the impact of relocation on drivers' performance and earnings. These findings uncover several actionable strategies for platforms aiming to enhance efficiency.

First, *balance enhancing* relocations improve driver performance and the match between supply and demand, benefiting the platform and increasing overall system utility. Thus, platforms should minimize *balance diminishing* relocations. The platform might assign fewer orders to drivers who have relocated longer distances to balanced clusters and focus on encouraging *HR-NFR* drivers to relocate toward imbalanced clusters. Second, drivers relocate to familiar areas, which moderates the effects of relocation. Hence, it is beneficial to have a nuanced understanding of driver location affinity, which anchoring behavior influences. The starting clusters (from which they begin their workday) during the first week of their work have a strong anchoring effect. On average, drivers deliver 28.5% of their orders from these starting clusters. The platform can manage cluster affinity by nudging new drivers to start their workdays from mostly imbalanced clusters to enhance system efficiency. Further, this number increases to 31.9% for *HR-FR*, and by generating the affinity of clusters within a smaller radius, the platform can move them to the most efficient category, LR-FR. Interestingly, the starting clusters of the first week also become a significant portion of the top 10% clusters for a driver in terms of the number of orders delivered. Third, making the *LR-NFR* category of drivers aware of the potential benefits of *familiar_relocation* can shift them to the most efficient category, *LR-FR*. Finally, the platform could send motivational nudges to drivers following extended relocations to counteract the impact on their performance. These strategies are feasible, requiring only additional parameters in the existing order allocation algorithm, and have the potential to improve operational dynamics significantly. It will be interesting to implement these solutions in a field setting.

The study's implications extend beyond individual performance and earnings. With global legislative trends favoring improved conditions for gig economy workers,[23] platforms will likely adjust staffing to reduce costs. This shift makes operational efficiency crucial, emphasizing the need for drivers to maximize order fulfillment rate rather than distributing orders among more drivers. Additionally, as platforms

[23] https://www.straitstimes.com/asia/se-asia/countries-around-the-world-advancing-benefits-and-protections-for-gig-workers

prioritize delivery speed, any decrease can impact not just driver performance[24] but also customer satisfaction and service quality. *Relocation distance* hurts driver performance and earnings, making it a critical factor to consider when optimizing system efficiency. Understanding and effectively managing relocation becomes essential for platform sustainability and service excellence.

To our knowledge, this study is the first to establish the significance of the effort allocated during SLT in optimizing system efficiency. We hope it will serve as a foundation for future research to explore the intricate relationship between SLT, workers' decision-making processes, operational parameters, and their collective impact on business performance. While our analysis focuses on food delivery platforms, the insights gained apply to other gig economy platforms that necessitate workers to allocate effort in the search for tasks during SLT, such as ride-hailing and taxi services. For instance, computer scientists have developed a Driver Guidance System to enhance the efficiency of taxi services and reduce SLT and relocation because the taxi industry is highly regulated, making surge pricing and demand aggregation unviable options (Cheng et al. 2018). However, even with the highest computation power and assuming 100% adherence to the guidance system, the reduction in relocation diminishes over time. Hence, managing relocation behavior from the drivers' perspective is crucial for optimizing performance.

References

Afèche P, Liu Z, Maglaras C (2023) Ride-Hailing Networks with Strategic Drivers: The Impact of Platform Control Capabilities on Performance. *Manufacturing & Service Operations Management*.

Allon G, Chen D, Moon K (2023a) Measuring Strategic Behavior by Gig Economy Workers: Multihoming and Repositioning. (April 17) https://papers.ssrn.com/abstract=4411974.

Allon G, Cohen MC, Sinchaisri WP (2023b) The Impact of Behavioral and Economic Drivers on Gig Economy Workers. *Manufacturing & Service Operations Management*.

Angrist JD, Imbens GW, Rubin DB (1996) Identification of Causal Effects Using Instrumental Variables. *Journal of the American Statistical Association* 91(434):444–455.

Antonakis J, Bendahan S, Jacquart P, Lalive R (2014) *Causality and Endogeneity* (Oxford University Press).

Ashkrof P, Correia GH de A, Cats O, van Arem B (2020) Understanding ride-sourcing drivers' behaviour and preferences: Insights from focus groups analysis. *Research in Transportation Business & Management* 37:100516.

Baer MD, Dhensa-Kahlon RK, Colquitt JA, Rodell JB, Outlaw R, Long DM (2015) Uneasy Lies the Head that Bears the Trust: The Effects of Feeling Trusted on Emotional Exhaustion. *Academy of Management Journal* 58(6):1637–1657.

Bechtold SE, Janaro RE, Sumners DWL (1984) Maximization of Labor Productivity Through Optimal Rest-Break Schedules. *Management Science* 30(12):1442–1458.

Bechtold SE, Thompson GM (1993) Optimal Scheduling of a Flexible-Duration Rest Period for a Work Group. *Operations Research*.

Beer R, Qi A, Ríos I (2024) Behavioral Externalities of Process Automation. (April 9) https://papers.ssrn.com/abstract=4295527.

[24] We strictly and actively discourage breaking speed limits. All these analyses are within speed limit. Also, slowing down within speed limit is not good for driver safety.

Benjaafar S, Hu M (2020) Operations management in the age of the sharing economy: What is old and what is new? *Manufacturing and Service Operations Management* 22(1):93–101.
Besbes O, Castro F, Lobel I (2021) Surge Pricing and Its Spatial Supply Response. *Management Science* 67(3):1350–1367.
Bimpikis K, Candogan O, Saban D (2019) Spatial pricing in ride-sharing networks. *Operations Research* 67(3):744–769.
Bobroske K, Freeman M, Huan L, Cattrell A, Scholtes S (2022) Curbing the Opioid Epidemic at Its Root: The Effect of Provider Discordance After Opioid Initiation. *Management Science* 68(3):2003–2015.
Bollinger B, Burkhardt J, Gillingham KT (2020) Peer Effects in Residential Water Conservation: Evidence from Migration. *American Economic Journal: Economic Policy* 12(3):107–133.
Bollinger B, Gillingham K (2012) Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Marketing Science* 31(6):900–912.
Bramoullé Y, Djebbari H, Fortin B (2009) Identification of Peer Effects Through Social Networks. *Journal of Econometrics* 150(1):41–55.
Brodsky A, Amabile TM (2018) The downside of downtime: The prevalence and work pacing consequences of idle time at work. *Journal of Applied Psychology* 103(5):496–512.
Buell RW, Cai W, Sandino T (2022) Learning or Playing? The Effect of Gamified Training on Performance. (December 8) https://papers.ssrn.com/abstract=4307211.
Burbano VC, Chiles B (2021) Mitigating Gig and Remote Worker Misconduct: Evidence from a Real Effort Experiment. *Organization Science*.
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.
Castillo VE, Mollenkopf DA, Bell JE, Esper TL (2022) Designing technology for on-demand delivery: The effect of customer tipping on crowdsourced driver behavior and last mile performance. *Journal of Operations Management* 68(5):424–453.
Chan TY, Chen Y, Pierce L, Snow D (2021) The Influence of Peers in Worker Misconduct: Evidence from Restaurant Theft. *Manufacturing & Service Operations Management* 23(4):952–973.
Chen DL, Horton JJ (2016) Are online labor markets spot markets for tasks? A field experiment on the behavioral response to wage cuts. *Information Systems Research* 27(2):403–423.
Chen X, Li Z, Ming L, Zhu W (2022) The Incentive Game Under Target Effects in Ridesharing: A Structural Econometric Analysis. *Manufacturing & Service Operations Management* 24(2):972–992.
Cheng SF, Jha SS, Rajendram R (2018) Taxis Strike Back: A Field Trial of the Driver Guidance System. *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*. AAMAS '18. (International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC), 577–584.
Cho DD, Bretthauer KM, Cattani KD, Mills AF (2019) Behavior Aware Service Staffing. *Production and Operations Management* 28(5):1285–1304.
Choudhary V, Sen P (2021) When Cost-Cutting May Go Wrong? Evidence from a Natural Experiment in Food Delivery. (July 2) https://papers.ssrn.com/abstract=3878609.
Dai H, Swaminathan JM, Xu Y (2022) Leveraging the Experience: Exploration and Exploitation in Gig Worker Learning Process. (May 11) https://papers.ssrn.com/abstract=4106978.
Donohue K, Özer Ö, Zheng Y (2020) Behavioral operations: Past, present, and future. *Manufacturing and Service Operations Management* 22(1):191–202.
Duong HL, Chu J, Yao D (2023) Taxi Drivers' Response to Cancellations and No-Shows: New Evidence for Reference-Dependent Preferences. *Management Science* 69(1):179–199.
Feng G, Kong G, Wang Z (2021) We Are on the Way: Analysis of On-Demand Ride-Hailing Systems. *Manufacturing & Service Operations Management* 23(5):1237–1256.
Freeman M, Robinson S, Scholtes S (2021) Gatekeeping, Fast and Slow: An Empirical Study of Referral Errors in the Emergency Department. *Management Science* 67(7):4209–4232.

Gallino S, Karacaoglu N, Moreno A (2022) Need for Speed: The Impact of In-Process Delays on Customer Behavior in Online Retail. *Operations Research* (May).

Ghose A, Han SP (2011) An Empirical Analysis of User Content Generation and Usage Behavior on the Mobile Internet. *Management Science* 57(9):1671–1691.

Gläser S, Jahnke H, Strassheim N (2021) Opportunities and Challenges of Crowd Logistics on the Last Mile for Courier, Express and Parcel Service Providers – a Literature Review. *International Journal of Logistics Research and Applications* 0(0):1–29.

Green LV, Savin S, Savva N (2013) "Nursevendor problem": Personnel staffing in the presence of endogenous absenteeism. *Management Science* 59(10):2237–2256.

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.

Halbesleben JRB, Bowler WmM (2007) Emotional exhaustion and job performance: The mediating role of motivation. *Journal of Applied Psychology* 92(1):93–106.

Halbesleben JRB, Neveu JP, Paustian-Underdahl SC, Westman M (2014) Getting to the "COR": Understanding the Role of Resources in Conservation of Resources Theory. *Journal of Management* 40(5):1334–1364.

Hanushek EA, Kain JF, Markman JM, Rivkin SG (2003) Does Peer Ability Affect Student Achievement? *Journal of Applied Econometrics* 18(5):527–544.

He S, Qiu L, Cheng X (2022) Surge Pricing and Short-Term Wage Elasticity of Labor Supply in Real-Time Ridesharing Markets. *Management Information Systems Quarterly* 46(1):193–228.

Heath C, Tversky A (1991) Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty* 4(1):5–28.

Hidi S (2016) Revisiting the Role of Rewards in Motivation and Learning: Implications of Neuroscientific Research. *Educational Psychology Review* 28(1):61–93.

Hobfoll SE (1989) Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist* 44(3):513–524.

Hobfoll SE (2001) The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. *Applied Psychology* 50(3):337–421.

Hobfoll SE, Halbesleben J, Neveu JP, Westman M (2018) Conservation of Resources in the Organizational Context: The Reality of Resources and Their Consequences. *Annual Review of Organizational Psychology and Organizational Behavior* 5(1):103–128.

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.

Ibanez MR, Clark JR, Huckman RS, Staats BR (2018) Discretionary Task Ordering: Queue Management in Radiological Services. *Management Science* 64(9):4389–4407.

Jahanshahi H, Bozanta A, Cevik M, Kavuk EM, Tosun A, Sonuc SB, Kosucu B, Başar A (2022) A deep reinforcement learning approach for the meal delivery problem. *Knowledge-Based Systems* 243:108489.

Jeon HH, Kim SH, Song H, Kim K, Cho S, Hong JH (2024) Redesigning Shift Work to Incorporate Heterogeneous Worker Preferences. (March 6) https://papers.ssrn.com/abstract=4750664.

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.

Kabra A, Belavina E, Girotra K (2020) Bike-Share Systems: Accessibility and Availability. *Management Science* 66(9):3803–3824.

Kamalahmadi M, Yu Q, Zhou YP (2021) Call to Duty: Just-in-Time Scheduling in a Restaurant Chain. *Management Science* 67(11):6751–6781.

KC D, Tushe S (2021) The Effects of Multisiting on Productivity and Quality. *Manufacturing & Service Operations Management* 23(4):803–818.

KC DS, Staats BR, Kouchaki M, Gino F (2020) Task Selection and Workload: A Focus on Completing Easy Tasks Hurts Performance. *Management Science* 66(10):4397–4416.

KC DS, Terwiesch C (2009) Impact of Workload on Service Time and Patient Safety: An Econometric Analysis of Hospital Operations. *Management Science* 55(9):1486–1498.

Koopman J, Lanaj K, Scott BA (2016) Integrating the Bright and Dark Sides of OCB: A Daily Investigation of the Benefits and Costs of Helping Others. *Academy of Management Journal* 59(2):414–435.

Larkin I, Pierce L, Gino F (2012) The psychological costs of pay-for-performance: Implications for the strategic compensation of employees. *Strategic Management Journal* 33(10):1194–1214.

Li S, Tavafoghi H, Poolla K, Varaiya P (2019) Regulating TNCs: Should Uber and Lyft set their own rules?

Liu TX, Yang J, Adamic LA, Chen Y (2014) Crowdsourcing with all-pay auctions: A field experiment on Taskcn. *Management Science* 60(8):220–237.

Ma TY, Rasulkhani S, Chow JYJ, Klein S (2019) A dynamic ridesharing dispatch and idle vehicle repositioning strategy with integrated transit transfers. *Transportation Research Part E: Logistics and Transportation Review* 128:417–442.

Manski CF (1993) Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies* 60(3):531.

Mao W, Ming L, Rong Y, Tang CS, Zheng H (2022) On-Demand Meal Delivery Platforms: Operational Level Data and Research Opportunities. *Manufacturing & Service Operations Management* 24(5):2535–2542.

Meng L, Batt RJ, Terwiesch C (2021) The Impact of Facility Layout on Service Worker Behavior: An Empirical Study of Nurses in the Emergency Department. *Manufacturing & Service Operations Management* 23(4):819–834.

Ricciardi V (2008) The Psychology of Risk: The Behavioral Finance Perspective. *Handbook of Finance*. (John Wiley & Sons, Ltd).

Roels G, Staats BR (2021) OM Forum—People-Centric Operations: Achievements and Future Research Directions. *Manufacturing & Service Operations Management* 23(4):745–757.

Stock J, Yogo M (2005) Testing for Weak Instruments in Linear IV Regression. Andrews DWK, ed. *Identification and Inference for Econometric Models*. (Cambridge University Press, New York), 80–108.

Tan TF, Netessine S (2014) When Does the Devil Make Work? An Empirical Study of the Impact of Workload on Worker Productivity. *Management Science* 60(6):1574–1593.

Wang C, Chen J, Xie P (2022) Observation or interaction? Impact mechanisms of gig platform monitoring on gig workers' cognitive work engagement. *International Journal of Information Management* 67:102548.

Wang Y, Lin X, He F, Xu Z, Shen ZJM (2023) On the Relocation Game of Ride-Hailing Platforms with Non-Atomic Drivers. (May 20) https://papers.ssrn.com/abstract=4454177.

Wooldridge JM (2002) *Econometric Analysis of Cross Section and Panel Data* (MIT Press).

Xu Y, Lu B, Ghose A, Dai H, Zhou W (2023) The Interplay of Earnings, Ratings, and Penalties on Sharing Platforms: An Empirical Investigation. *Management Science*:mnsc.2023.4761.

Zhang R, Zhang Y, Hu K, Zhao X (2023a) The Impact of Financial Incentives in Last-Mile Operations: An Empirical Investigation. (May 31) https://papers.ssrn.com/abstract=4465994.

Zhang W, Zheng Z, Cui R (2023b) Restaurant Density and Delivery Speed in Food Delivery Platforms. (April 14) https://papers.ssrn.com/abstract=4419279.

Zhao Y, Papier F, Teo CP (2024) Market Thickness in Online Food Delivery Platforms: The Impact of Food Processing Times. *Manufacturing & Service Operations Management*.

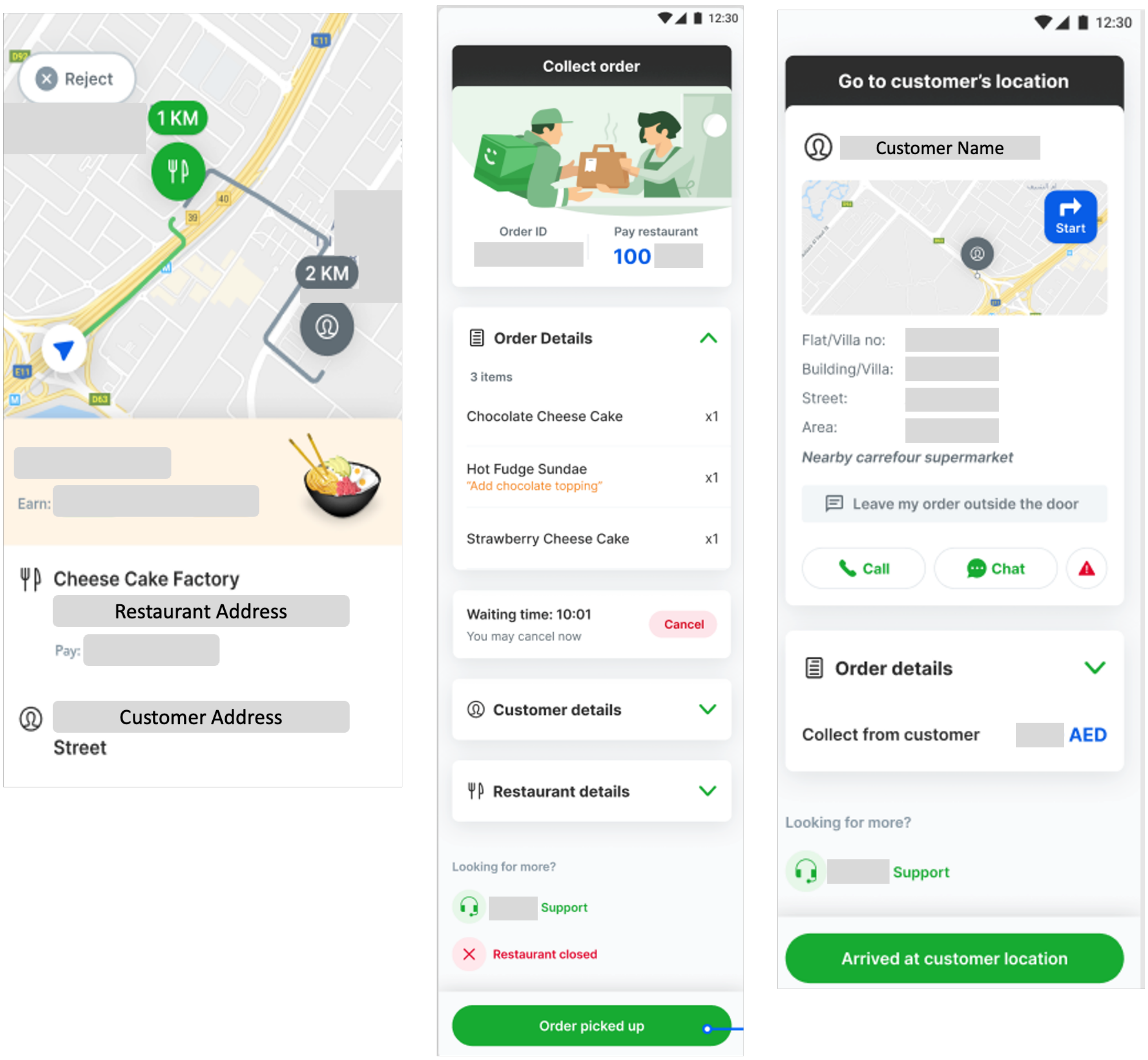
Zhou W, Zhu S, Cao P, Wu J (2023) Analysis of an on-demand food delivery platform: Participatory equilibrium and two-sided pricing strategy. *Journal of the Operational Research Society* 0(0):1–12.

Appendix 1

A1.1 Delivery Driver Smartphone App

Figure A.1: Screenshot of the driver smartphone app

a) Screenshot of Driver App **b) Driver App – Order Details** **c) Driver App – Customer Details**



A1.2 Pairwise Correlation & Distribution

Table A.1: Pairwise Correlation Matrix of Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1) relocation_distance	1.00											
2) balance_enhancing	-0.01*	1.00										
3) familiar_relocation	0.05*	0.15*	1.00									
4) tip	0.01*	0.01*	0.00*	1.00								
5) rst_delay	0.00*	-0.02*	0.00*	0.02*	1.00							
6) rst_delay.NH	-0.04*	0.02*	0.07*	0.02*	0.09*	1.00						
7) familiarity	-0.26*	0.06*	0.09*	0.01*	0.02*	0.09*	1.00					
8) earnings	0.36*	0.00*	-0.04*	0.02*	0.02*	-0.03*	-0.15*	1.00				
9)earnings_till_order	-0.07*	0.04*	0.11*	-0.01*	0.00	-0.09*	0.15*	-0.04*	1.00			
10)perc.SLT_till_order	0.00*	-0.02*	-0.02*	-0.01*	-0.03*	-0.09*	-0.01*	0.01*	0.04*	1.00		
11)pending_orders	-0.06*	0.06*	0.01*	0.00	0.08*	0.05*	0.07*	-0.01*	0.07*	0.02*	1.00	
12)orders_rst_area	-0.09*	0.22*	0.03*	0.03*	0.07*	0.14*	0.19*	0.01*	0.11*	0.00	0.17*	1.00
13)orders_cst_area	-0.20*	0.16*	0.02*	0.03*	0.06*	0.11*	0.41*	-0.06*	0.11*	0.02	0.14	0.57*

Note: $*p < 0.05$

Figure A.2: Distance Travelled by Driver in a Day

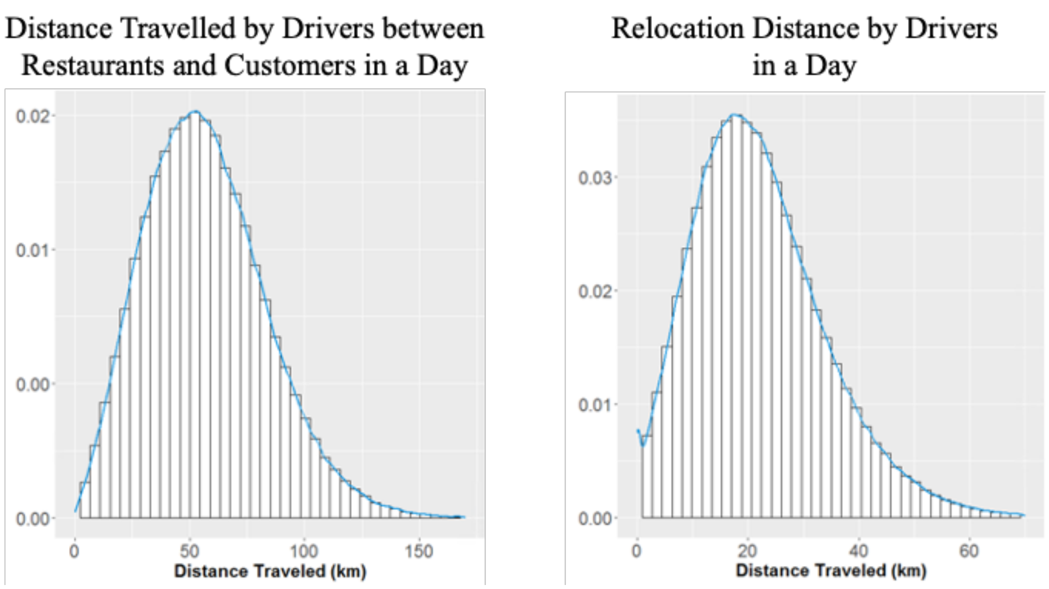
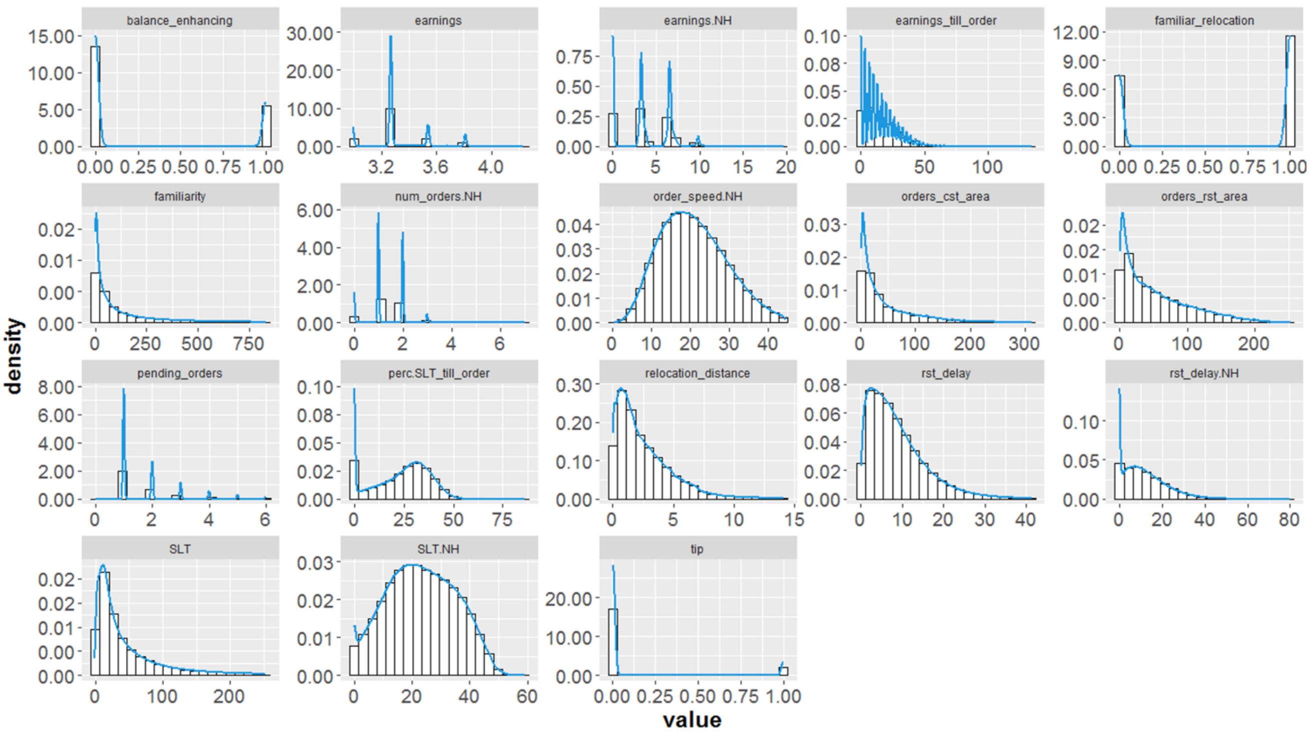


Figure A.3: Distribution Plots of Variables



Appendix 2

A2.1 Effect of Relocation on Performance and Earnings

Table A.2: OLS Estimates of Effect of Relocation on Performance and Earnings

	num_orders.NH	*order_speed.NH*	*SLT.NH*	*earnings.NH*
	(1)	(2)	(3)	(4)
relocation_distance	-0.005***	0.104***	0.022***	-0.262***
	(0.000)	(0.005)	(0.004)	(0.001)
tip	0.005***	-0.001	-0.082***	0.024***
	(0.001)	(0.014)	(0.019)	(0.004)
rst_delay	-0.003***	0.009***	0.022***	-0.010***
	(0.000)	(0.001)	(0.001)	(0.000)
rst_delay.NH	0.026***	0.044***	-0.653***	0.067***
	(0.000)	(0.001)	(0.002)	(0.000)
earnings	-0.023***	0.373***	-0.814***	0.312***
	(0.002)	(0.042)	(0.042)	(0.011)
earnings_till_order	-0.001***	0.039***	0.012***	0.021***
	(0.000)	(0.001)	(0.001)	(0.000)
familiarity	0.000***	0.000	0.002***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
pending_orders	0.002***	-0.016**	0.016**	0.034***
	(0.000)	(0.006)	(0.007)	(0.002)
orders_cst_area	0.000***	-0.005***	0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
orders_rst_area	0.000***	0.002***	-0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
perc.SLT_till_order	0.000***	0.011***	0.008***	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
adj-R^2	0.228	0.212	0.330	0.185
N	3,568,089	3,364,636	2,778,872	3,568,089

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with driver, date, cst_area, peak-hours, and weekend fixed effects.*

A2.2 First Stage of the Main Model

Table A.3: Stage 1 of 2SLS

	relocation_distance
	(1)
avg_co.relocation	0.455***
	(0.054)
tip	0.031***
	(0.003)
rst_delay	0.002***
	(0.000)
rst_delay.NH	-0.003***
	(0.000)
earnings	2.552***
	(0.018)
earnings_till_order	-0.004***
	(0.000)
familiarity	-0.003***
	(0.000)
pending_orders	-0.025***
	(0.002)
orders_cst_area	0.000*
	(0.000)
orders_rst_area	0.000
	(0.000)
perc.SLT_till_order	-0.004***
	(0.000)
adj-R^2	0.295
N	3,561,341
F-test stat	705.4

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

Appendix 3

A3.1 Alternative Treatment Variable

Table A.4: Alternative Treatment Variable

	num_orders.NH	*order_speed.NH*	SLT.NH	earnings.NH
	(1)	(2)	(3)	(4)
is_relocated	-0.575***	-6.104**	-1.466	-4.501***
	(0.139)	(2.625)	(2.612)	(0.816)
adj-R^2	0.069	0.109	0.326	-0.135
N	3,429,992	3,236,398	2,685,412	3,429,992

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

A3.2 Alternative Dependent Variables

Table A.5: Alternative Dependent Variables

	num_orders.PH.RD	*order_speed.RD*	earnings.PH.RD
	(1)	(2)	(3)
relocation_distance	-0.059***	-0.617**	-0.160***
	(0.015)	(0.292)	(0.049)
adj-R^2	0.259	0.286	0.263
N	3,390,464	3,313,602	3,390,173

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

A3.3 Sub-Sample of Relocations with Driver Working in the Next Hour

Table A.6: At least One Order in the Next Hour

	num_orders.NH	*order_speed.NH*	earnings.NH
	(1)	(2)	(3)
relocation_distance	-0.072***	-0.708**	-0.562***
	(0.017)	(0.295)	(0.090)
adj-R^2	0.181	0.183	0.144
N	3,429,992	3,236,398	3,429,992

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

A3.4 Impact of Relocations per Unit Busy Time in the Next Hour

Table A.7: Impact Per Unit Busy Time

	num_orders.BT.NH	earnings.BT.NH
	(1)	(2)
relocation_distance	-0.002***	-0.018***
	(0.001)	(0.003)
adj-R^2	0.071	0.083
N	2,685,412	2,685,412

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

A3.5 Coworkers Dependent Variable as Additional Control for Instrument Ignorability

Table A.8: Coworkers Dependent Variable as Additional Control

	num_orders.NH	earnings.NH
	(1)	(2)
relocation_distance	-0.075***	-0.286***
	(0.020)	(0.104)
Added Control	*co.num_orders.NH*	*co.earnings.NH*
adj-R^2	0.179	0.163
N	3,131,268	2,289,727

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, peak-hours, and weekend fixed effects.*

A3.6 Order Hour Fixed Effect Instead of Peak Hours

Table A.9: With Order Hour Fixed Effect

	num_orders.NH	*order_speed.NH*	*SLT.NH*	*earnings.NH*
	(1)	(2)	(3)	(4)
relocation_distance	-0.082***	-0.852***	-0.040	-0.678***
	(0.017)	(0.302)	(0.341)	(0.098)
adj-R^2	0.176	0.174	0.339	0.124
N	3,429,992	3,236,398	2,685,412	3,429,992

*Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in parentheses and clustered at the driver level. Estimated with instrumental variable using 2SLS with all controls and driver, date, cst_area, order hour, and weekend fixed effects.*