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Understanding multi-homing and switching by platform drivers

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ABSTRACT

Freelance drivers in the shared mobility market frequently switch or work for multiple platforms, affecting driver labor supply. Due to the importance of driver labor supply for the shared mobility market, understanding drivers' switching and multi-homing behavior is vital to managing service quality on – and effective regulation of – mobility platforms. However, a lack of individual-level data on driver behavior has thus far impeded a deeper understanding. This paper taxonomizes and estimates perceived switching and multi-homing frictions on mobility platforms. Based on a structural model of driver labor supply, we estimate switching and multi-homing costs in a platform duopoly using public and limited high-level survey data. Estimated costs are sizeable, and reductions in multi-homing and switching costs significantly affect platform market shares and driver welfare. Driver labor supply elasticity with respect to platform wage is also discussed considering both multi-homing and switching frictions.

1. Introduction

With the rapid development and popularization of mobile and wireless communication technologies, Transportation Network Companies (*TNCs*) have leveraged internet-based platforms to operate ride-sourcing services worldwide. Individual mobility in urban spaces increasingly relies on TNCs, which serve as intermediaries to match on-demand passengers and freelance drivers in real-time. A crucial difference between TNC platforms and traditional transportation services is that their success relies not only on demand from passengers but also on consistent labor supply by drivers. Therefore, it is vital to understand passenger demand (Grahn et al., 2020), driver supply, *and* trip characteristics (Li et al., 2019) for platforms to make better design and operational decisions and for policymakers to design effective regulations. This paper focuses on driver labor supply, particularly the role of platform *multi-homing* and *switching*.

In many TNC marketplaces, *driver multi-homing*, i.e., drivers' working for several TNCs simultaneously, is prevalent. For example, drivers in the US may work on Uber and Lyft simultaneously, and drivers in Southeast Asia may work on Grab and Go-Jek simultaneously (Yu et al., 2021; Valderrama and Cameron, 2023). Multi-homing from the passenger side can be found in Valderrama (2020). In addition, drivers often *switch* between primary platforms to optimize their working conditions. Understanding multi-homing and switching behavior – and corresponding drivers' labor supply decisions – are essential to operate TNCs, designing informed interventions, and designing transportation market regulation.

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Although understanding multi-homing and switching is desirable, limited data access impedes progress on it. Some previous studies of driver labor supply use fine-grained micro-level trip data from a single platform to calibrate or estimate their models (e.g., Sun et al. (2019), Rosaia (2020) and Cook et al. (2021)). However, accessing the information on drivers and their fine-grained working data on multiple platforms within a marketplace is challenging for TNCs, researchers, and regulators. TNCs need information on driver work on other – competing – platforms to understand driver multi-homing and switching, and regulators and researchers need information from multiple TNCs. In both cases, accessing fine-grained data on multiple platforms might be difficult.

Data access limitations necessitate an approach to understanding driver multi-homing and switching without platform-provided fine-grained data. In this paper, we taxonomize types of multi-homing and switching frictions; we propose a structural model for driver labor supply; and we estimate the model using public and limited survey data. Specifically, we use two data sources from a TNC duopoly in Jakarta, Indonesia: (i) drivers' aggregate working-hour allocation and earnings on two platforms and (ii) publicly available wage data as outside job options for drivers.

Our contributions are threefold:

- We discuss and categorize different sources and types of multi-homing and switching frictions faced by platform drivers in the shared mobility market.
- We propose a structural model to describe driver labor supply decisions in a TNC oligopoly.
- We estimate the proposed model using a limited high-level survey as well as publicly available data. The estimation uses a Markov chain Monte Carlo (MCMC) method to estimate a probit model. Using the model, we also investigate counterfactuals for changes in multi-homing and switching frictions on driver welfare, market shares, and supply elasticities.

The rest of the article is organized as follows. Related literature is reviewed in Section 2. Different types of multi-homing and switching frictions are taxonomized and discussed in Section 3. Section 4 describes the empirical strategy, which includes a structural model of driver supply and a Bayesian estimation framework. The data used in this paper are presented in Section 5. Section 6 reports estimation results and Section 7 conducts sensitivity and counterfactual analyses. Lastly, conclusions, limitations, and future research directions are discussed in Section 8.

2. Literature review

There is rich literature on the design and operations of TNC platforms in shared mobility markets. In this section, we review the literature in three areas: models and analyses of driver labor supply in shared-mobility markets; platform competition with multi-homing and switching; and empirical work in mobility markets.

2.1. Models and analyses of driver labor supply

The labor-supply choices of freelance drivers, specifically, drivers' participation and working decisions on two-sided platforms, are critical model components in most work regarding the design and operations of TNCs in shared mobility markets. Some studies focus on empirical analysis of driver labor supply when drivers can decide whether to participate and choose the number of working hours flexibly. For example, Sun et al. (2019) proposes an econometric framework with closed-form measures to estimate drivers' participation and working-hour elasticity. Similar to Chen and Sheldon (2016), they find empirical evidence that surge pricing incentivizes drivers to adjust their work schedules to align with periods of high demand. Some studies argue that drivers' behavior significantly impacts their earnings. For example, Chaudhari et al. (2018) design an earnings-maximization strategy for drivers and show that strategic labor supply significantly affects drivers' earnings.

Another strand of relevant literature examines operations and pricing for shared transportation platforms. While some work assumes that drivers follow platform recommendations (e.g., Bertsimas et al. (2019), Alonso-Mora et al. (2017), Braverman et al. (2019), Wen et al. (2017), Lyu et al. (2023), Zhang and Masoud (2021), Guo et al. (2021, 2022) and Lei et al. (2018)), other studies assume Bayes-rational freelance drivers. For example, Bai et al. (2019) proposes a queuing model to optimize platforms' profit while considering price-sensitive customers and earnings-sensitive drivers. In their model, drivers provide service only if their earning rate exceeds a reservation earnings rate. Taylor (2018) evaluates the impact of uncertainty in passenger delay sensitivity and driver independence on platforms' optimal service price and wage. As in Bai et al. (2019), each driver has an opportunity cost, and the driver will participate on the platform when they earn more than an opportunity cost. Zha et al. (2017) propose equilibrium models to characterize driver labor supply. Because of competing theories regarding how drivers determine their working hours, they present equilibrium models with neoclassical or income-targeting hypotheses regarding drivers' working behavior. Jiang et al. (2021) show that regret aversion and ignorance of suggestion are the two major behavioral factors influencing drivers' repositioning decisions. Zhu et al. (2021) assumes that drivers use a Markov decision process to choose work and relocation decisions to maximize their long-term earnings. Other example of labor supply models are Cachon et al. (2017), Zha et al. (2017), Yan et al. (2020), Ke et al. (2020), Bimpikis et al. (2019), Xu et al. (2020), Yang et al. (2020), Urata et al. (2021), Dong et al. (2021), Zhang and Nie (2021), Bahrami et al. (2022) and Battifarano and Qian (2019).

In these studies, some do not model multi-homing or switching decisions (e.g., Loginova et al. (2022)) and others assume that in moments in which drivers join one platform, they have exact knowledge of the surplus gained and the prices multiple platforms provide (e.g., Teh et al. (2023)). Compare (Wang and Yang, 2019) for a comprehensive review of ride-sourcing systems, including from demand, supply, and platform perspectives. Similar problems exist in a more general context of transportation-enabled urban services (e.g., see Wang (2022) and Bahrami et al. (2021)). In contrast to the present paper, driver labor supply studies typically do not explicitly model frictions from multi-homing and switching.

2.2. Platform competition with multi-homing and switching

Multiple TNCs may exist and compete in a local market. They compete not only on the demand side for passengers but also on the supply side for flexible self-scheduling drivers who may work for multiple platforms. The related work on platform competition with multi-homing and switching is mostly theoretical. The paper Zhou et al. (2022) describe the equilibrium of a competitive ride-sourcing market with platform integration. They compare two market structures, with and without platform integration, and find that platform integration enhances social welfare by eliminating market fragmentation costs. However, integration does not necessarily increase platform profit. Jeitschko and Tremblay (2020) consider two-sided markets in which consumers and firms choose whether to single-home (patronize only one platform) or multi-home (join competing platforms concurrently). They find that, in equilibrium, consumers single-home and firms multi-home. Tadepalli and Gupta (2020) present a model of rival ride-sharing platforms to assess the effects of multi-homing on drivers and customers alike. The study concludes that multi-homing may provide temporary advantages, but ultimately prove detrimental to all market participants. Other work on platform competition with multi-homing includes Bryan and Gans (2019), Belleflamme and Peitz (2019), Bakos and Halaburda (2020) and Lian et al. (2021). Klemperer (1987) and Farrell and Shapiro (1988) introduce the effects of consumer switching costs in competition. Klemperer (1987) provides a taxonomy of switching costs into *transaction costs*, *learning* costs, and *artificial* switching costs, a taxonomy we will adopt and extend to multi-homing costs. We will discuss these types and their distinctions in Section 3. In contrast to these theoretical studies, the present paper estimates market frictions from data.

2.3. Empirical work in mobility markets

Much of the empirical work in shared mobility markets uses micro-level data. For example, Chen et al. (2019) use data on hourly earnings and driving from Uber to document driver utilization of real-time flexibility. They measure the value of flexibility through time variation in drivers' reservation wages and estimate surplus and labor supply in freelancing and an employment work relationship counterfactual. Rosaia (2020) studies a TNC duopoly in New York City. The paper proposes a dynamic model of competition, and uses trip-level data to estimate the impact of a TNC merger and entry regulation. The paper carefully matches driving signatures on different platforms to identify the multi-homing patterns of TNC drivers. Cook et al. (2021) use micro-level data to identify a gender pay gap in the gig economy, which they attribute to three factors: experience on the platform (learning-by-doing); preferences and constraints over where to work (primarily driven by where drivers live, and, to a lesser extent, safety); and preferences for driving speed. An additional area of research is focused on quantifying the efficiency loss induced by the market segmentation in the shared mobility market (Guo et al., 2023; Zhang et al., 2022; Wang et al., 2023). Guo et al. (2023) propose four market structures with the goal of mitigating market inefficiency in a duopoly TNC market. They utilize micro-level data to substantiate the effectiveness of their proposed market frameworks.

Multi-homing and switching frictions (which we will also call *costs* or *perceived costs* in the following) are important, yet not associated with particular channels of affecting driver choices. The next section taxonomizes different sources of multi-homing and switching costs using notions from Economics, Klemperer (1987). This taxonomy allows for the concrete regulator and TNC interventions even if our estimates only yield perceived costs for switching and multi-homing.

3. A taxonomy of switching and multi-homing frictions

Before proposing the empirical model, we taxonomize sources for multi-homing and switching costs. When a driver works for a TNC that is not their initial platform, they perceive switching costs; when a driver engages in multiple platforms, they perceive both switching and multi-homing costs. In more specific terms, upon joining an alternative platform, we posit that drivers encounter a disutility from such switching, denoted as a switching cost. If they maintain concurrent service on their initial platform simultaneously, they encounter an additional disutility from such multi-homing, denoted as a multi-homing cost. We provide illustrative examples for each scenario and argue that both switching and multi-homing costs are expected to be non-negative.

3.1. Switching costs

Klemperer (1987) identifies three types of switching costs in consumer product choice: *transaction*, *learning*, and *artificial* costs. We apply and interpret its typology for switching cost in the shared urban mobility context, and add a fourth source due to *psychological* factors important to platform choice. Some types of costs have similar meanings for consumers and TNC drivers, e.g., transaction cost, others have specific relevance for TNC drivers.

3.1.1. Transaction costs

Even if the work environment on two TNC platforms might be very similar, switching from one platform to another is associated with "moving" costs. For example, installing an app, undergoing a background check by an agency, obtaining a TNC driver permit, and forgoing income while waiting for a driver's permit are examples of transaction costs before signing up to drive for a platform. When moving onto a new platform, fees to upgrade or rent a vehicle that meets the platform's specific requirements also accounts for additional transaction costs.

The magnitude of transaction costs for TNC drivers likely varies across markets. In less regulated markets, a driver might only need to install an app and set up a payment system to start working as a TNC driver. In contrast, regulatory requirements might lead to much higher transaction costs in a highly regulated market. The difference in the expected magnitude of transaction costs also affects the viability of associated cost reductions. It might be hard to meaningfully reduce transaction costs in an unregulated market in absolute terms, but possible in highly regulated markets due to differences in baseline cost levels.

3.1.2. Learning costs

A second form of switching cost arises from a need to *learn* how to properly use a new platform. Even functionally equivalent TNC apps might require learning. For example, interface differences might lead to different trip acceptance and rejection flows, communication with riders, and information on surge prices. Using a platform productively requires digital literacy, which is an important determinant of learning costs. For frequent users of information technology, understanding the functionalities of a competing platform after working on another platform might not be costly.

Learning how to work optimally, given platform-specific demand patterns, might be more challenging. For instance, Ashkrof et al. (2020) quotes a focus group participant highlighting the importance of demand knowledge for earnings and its connection to the experience.[2] Learning about demand might be harder in particular if demand is heterogeneous across platforms. Such heterogeneity also arises when a TNC entering a market might attract a different composition of passengers from the incumbent.

3.1.3. Artificial costs

Even with equivalent working experience and the same payment structure across platforms, switching is still costly because the wage paid to drivers typically depends on their status or seniority level on each platform. For example, drivers may be awarded a higher status with a bonus if they serve a required number of weekly rides. Also, they may obtain a higher seniority level if they keep working on a platform for a month, reducing the platform's commission. Drivers who start working for a new platform might miss out on the payment they would have obtained if they had continued working for their previous platform.

This type of artificial switching cost depends on platforms' payment structure and intersects with their incentive design.

3.1.4. Psychological costs

Some (perceived) switching costs for TNC drivers might not be covered by Klemperer (1987)'s typology. For example, cost associated with an equivalence to *brand loyalty* in consumer studies (see, e.g., Kuehn (1962) and Wernerfelt (1991)) might also apply to TNC drivers. Wernerfelt (1991) distinguishes two kinds of brand loyalty factors: inertial and cost-based. Interpreted in the context of shared mobility markets, inertially brand-loyal drivers are slow to learn about the value of another platform. Cost-based drivers are biased toward their "default" platform, which could be, for example, those that close social contacts of drivers use. Note that learning the value of another platform is different from the cost perceived in learning costs, which is about *how* to use a platform, not about *how good* the platform is.

Given the long time frame we assume for drivers who switch between platforms, inertial effects in Wernerfelt (1991)'s typology are unlikely, whereas cost-based effects are possible, and might be important policy levers.

3.2. Multi-homing costs

Working on multiple platforms simultaneously imposes (perceived) costs on drivers beyond and is different from switching costs. In order to start working on an additional platform, drivers first need to bear the switching costs discussed above and also suffer other additional costs, which we discuss here. Similar to switching costs, we also categorize using a typology following Klemperer (1987): *transaction costs*, *learning costs*, *artificial costs*, and *psychological costs*.

3.2.1. Transaction costs

Multi-homing requires additional effort from drivers, which may dissuade them from doing so. This includes logging off of one TNC's app and on to another or acquiring a second phone to run the apps simultaneously and reject trips for one TNC when working for the other. Even when running two apps on the same phone, the required cellular data volume for frequent location transmission to TNC servers is much higher. It might necessitate a cellular plan with higher data volume for drivers. Note that the costs listed here are in addition to switching transaction costs, which focus on signup and obtaining a driver's permit.

3.2.2. Learning costs

Multi-homing is challenging for drivers to manage and requires process learning. While some third-party service providers integrate multiple TNC platforms into a single app for passengers on the market demand side, there is no such integrator for drivers on the supply side. Hence, drivers need to learn to effectively multi-home on different platforms *and* learn to use a new mobile application, which is the source of switching learning costs.

3.2.3. Artificial costs

Artificial multi-homing costs due to platforms' contractual design with drivers might be significant. First, marginal payment by platforms tends to be non-constant and increasing. These render earnings from serving x rides less than half the earnings from serving $2x$ rides on the same platform. Rejecting or delaying the response to an assigned ride from one platform when multi-homing may incur a penalty and loss of bonuses for drivers, who may perceive these costs as even higher than the actual amount. Multi-homing artificial costs are closely related to the corresponding switching cost, which also depend on the reimbursement structure of the TNCs.

[2] Quote: "It's just experience. I've driven for Uber for so long and I've driven as a street taxi, so I know everything. You just have to know where to stand".

3.2.4. Psychological costs

Psychological factors might also prevent drivers from multi-homing, in addition to those that affect drivers who start to work for a new TNC. Many TNC drivers have previously worked as taxi drivers, in a model where they worked for a single taxi company. Having experience with a similar work environment in a classical employment relationship might make single-homing seem more natural for such drivers.

4. Empirical strategy

Before introducing a structural model and estimation, we discuss data access in shared mobility markets.

4.1. Data access in shared mobility markets

Data are valuable in shared mobility markets, and crucial for decision-making by several stakeholders, including TNCs, regulators, and researchers. TNCs, for example, derive better design and operational strategies from data. However, each platform usually only has access to its data, and it is challenging to get data on labor supply from competing TNCs. Regulators use data to design policies that lead to the healthy development of shared mobility markets. For researchers, data are required to test hypotheses and develop academic or engineering models, which drive technological advancements for shared mobility platforms. Nonetheless, regulators and researchers are typically granted access to only macro-level aggregate data or work with a single TNC. In both cases, data on multiple platforms is limited. Hence, data access in shared mobility markets is costly for several stakeholders in the shared mobility market.

An ideal dataset to facilitate the research on multi-homing and switching by platform drivers in shared mobility markets should contain drivers' detailed working records on multiple platforms – including their service orders in sequence, trajectories, earnings, service times, and switching times between all platforms – and passengers' complete order histories. With fine-grained data on all individual drivers across platforms, we could observe and understand how drivers make decisions regarding which platform(s) to work on, how to allocate their working hours, when to switch between platforms, and how market frictions (including switching and multi-homing costs) impact these decisions. However, such data might not be available. Therefore, designing an approach to address these questions using only limited, easily collectible, data has practical relevance.

Taking this limited data accessibility seriously, we propose a model to reflect drivers' decision-making under perceived multi-homing and switching costs in a duopoly shared mobility market. Based on the model, we introduce a framework to estimate the costs using public and limited high-level data, which only contains drivers' working-hour allocation between platforms and publicly available wage data. Such data can easily be collected using driver surveys and census information.

4.2. Model

Drivers $i = 1,2,\dots,n$ decide their working hours for TNCs $j = 1,2,\dots,p$. (In the following, we consider mostly a duopoly, with TNCs A = Go-Jek and B = Grab.) We denote driver i's initial TNC by j_i. Drivers choose to allocate their $\overline{h}$ daily working hours in an observation period. Given a set of TNCs $L \subseteq \{1,2,\dots,p\}$ driver i works for, the driver split $\overline{h}$ between working hours h_{ijL}, $j = 1,2,\dots,p$, earning a reimbursement of $Q_{ijL} = Q_j(h_{ijL}) + \epsilon'_{ijL}$, and an outside option, which yields them a constant marginal utility of o. We assume that the error terms in the payment, i.e., ϵ'_{ijL}, are independent for different platforms. If a driver chooses to work a positive number of hours for TNC j, we describe that they *work* for that TNC j. If a driver chooses to work for a TNC different from j_i, they incur a disutility of $s_{j_ij'} > 0$ for some $j' = 1,2,\dots,p$ and $j' \neq j_i$. If they choose to work for a non-singleton subset of companies $L \subseteq \{1,2,\dots,p\}$ with $|L| \geq 2$, they incur an additional disutility of $m_L > 0$. We consider a duopoly in the focal market, leading to only one non-singleton set. In this case, we denote $m = m_{\{1,2\}}$. Drivers have quasi-linear utilities and perceive additive utility for switching companies. Assuming that a driver i works for a subset of TNCs L, they receive a utility

$$V_{iL} = \sum_{j\in L} Q_j(h_{ijL}) + o\left(\overline{h} - \sum_{j\in L} h_{ijL}\right) - \sum_{j\in L\setminus\{j_i\}} s_{j_ij} - m_L \mathbb{1}_{|L|\geq 2} + \epsilon_{iL}. \tag{1}$$

Here, ϵ_{iL} contains the error terms ϵ'_{ijL} and additional error terms on the multi-homing and switching costs, and h_{ijL} are the working hours of driver i initially on TNC j when working for the set of TNCs L. $\mathbb{1}_{|L|\geq 2}$ is an indicator function representing whether driver i works for more than one platform at the same time. In the case of a duopoly, this leads to three cases where drivers work for at least one platform. Let $j' \neq j_i$ be the platform that a driver did not initially work for:

$$V_{i\{j_i\}} = Q_{j_i}(h_{ij_i\{j_i\}}) + o\cdot(\bar{h} - h_{ij_i\{j_i\}}) + \epsilon_{i\{j_i\}}, \tag{2a}$$

$$V_{i\{j'\}} = Q_{j'}(h_{ij'\{j'\}}) + o\cdot(\bar{h} - h_{ij'\{j'\}}) - s_{j_ij'} + \epsilon_{i\{j'\}}, \tag{2b}$$

$$V_{i\{j_i,j'\}} = Q_{j_i}(h_{ij_i\{j_i,j'\}}) + Q_{j'}(h_{ij'\{j_i,j'\}}) + o\cdot(\bar{h} - h_{ij_i\{j_i,j'\}} - h_{ij'\{j_i,j'\}}) - s_{j_ij'} - m + \epsilon_{i\{j_i,j'\}}. \tag{2c}$$

(Eq. (2a)) is the utility for only working for the TNC j_i that the driver initially working for. (Eq. (2b)) corresponds to changing to TNC j' fully. (Eq. (2c)) represents that the driver multi-home on both platforms. We assume that the marginals of the errors $(\epsilon_{iA})_{A\subseteq\{1,2,\dots,p\}}$ are centered Gaussians, and distributed with covariance matrix $\boldsymbol{\Sigma} \in \mathbb{R}^{|C|\times|C|}$, where C is the set of possible choices for drivers.

4.3. Estimation

In our estimation, we consider the duopoly model with two TNCs A and B. We denote $M := \{A, B\}$, hence, choice set $C = \{A, B, M\}$. For the model simplicity, let s and $\tilde{s}$ represent the switching cost from platform A to B and from platform B to A, respectively. As in the general model, we determine multi-homing and switching costs as fundamental variables that impact the desirability of a particular option, consequently affecting the decisions of drivers regarding their labor supply. To attain these estimations, we employ a Bayesian estimation approach that generates estimates of multi-homing and switching costs, maximizing the likelihood of the collected data and choices made by drivers. This allows us to refine and enhance our understanding of these crucial factors within the framework.

With the specification of the TNC set M and the choice set C, the utility model for a driver i who initially works for platform A can be written as:

$$V_{iA} = Q_A(h_{iA\{A\}}) + o \cdot (\bar{h} - h_{iA\{A\}}) + \epsilon_{i\{A\}}, \tag{3a}$$

$$V_{iB} = Q_B(h_{iB\{B\}}) + o \cdot (\bar{h} - h_{iB\{B\}}) - s + \epsilon_{i\{B\}}, \tag{3b}$$

$$V_{iM} = Q_A(h_{iA\{M\}}) + Q_B(h_{iB\{M\}}) + o \cdot (\bar{h} - h_{iA\{M\}} - h_{iB\{M\}}) - s - m + \epsilon_{i\{M\}}. \tag{3c}$$

The utility specification for drivers who initially work for platform B can be formulated in a similar way by considering the switching cost $\tilde{s}$. Besides the standard normal-distributed random errors in the utility model (3), multi-homing and switching costs $m, s, \tilde{s}$ are variables that need to be estimated.

Denote by y_{ij} the decision made by driver i about option j, which is known from the data, i.e.,

$$y_{ij} = \begin{cases} 1 & \text{if } V_{ij} \geq V_{ij'},\ \forall j' \in \{A,B,M\}, \text{ and} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

This reduces the choice of which platform to work for to a multinomial probit (MNP) model, as in the discrete-choice analysis (Bolduc, 1999). Using the standard approach in MNP, we deal with *additive redundancy* by subtracting the utility specification of one baseline choice from other choices and handle *multiplicative redundancy* by normalizing the first error term.[3] This yields a model

$$\boldsymbol{U}_i^* = \begin{bmatrix} V_{iA} - V_{iM} \\ V_{iB} - V_{iM} \end{bmatrix} = \boldsymbol{\beta_0} + \boldsymbol{X}_i^* \cdot \begin{bmatrix} m \\ s \\ \tilde{s} \end{bmatrix} + \boldsymbol{\eta}_i^*,\ \boldsymbol{\eta}_i^* \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Omega}^*), \tag{5}$$

where $\boldsymbol{X}_i^* \in \mathbb{R}^{2\times 3}$ stands for a data matrix for driver i, $\boldsymbol{\beta_0}$ represents the intercept, and $\boldsymbol{\Omega}^* \in \mathbb{R}^{2\times 2}$ is a covariance matrix with $\omega_{11}^* = \mathrm{var}(\epsilon_{iA} - \epsilon_{iM}) = \hat{a}$. To impose a positive definite error covariance matrix $\boldsymbol{\Omega}^*$, we aim to estimate a lower triangular matrix $\boldsymbol{S}$ with $s_{11} = \sqrt{\hat{a}}$ based on a Cholesky decomposition of $\boldsymbol{\Omega}^*$, i.e., $\boldsymbol{\Omega}^* = \boldsymbol{S}\boldsymbol{S}^T$. The parameters to be estimated in $\boldsymbol{S}$ are denoted as S_{21} and S_{22}. Then the estimable model can be formulated as

$$\boldsymbol{U}_i^* = \boldsymbol{\beta_0} + \boldsymbol{X}_i^* \boldsymbol{\beta} + \boldsymbol{S}\boldsymbol{w}_i^*,\ \boldsymbol{w}_i^* \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}_2), \tag{6}$$

where $\boldsymbol{I}_2$ is a (2×2) identity matrix and

$$\boldsymbol{\beta} = \begin{bmatrix} m \\ s \\ \tilde{s} \end{bmatrix}$$

denotes the vector of estimates. Furthermore, we introduce a (2×2) linear operator $\boldsymbol{M}_j$ that transforms vector $\boldsymbol{U}_i^*$ into $\boldsymbol{U}_i$, which denotes the utility differences of other options compared to the option j selected by driver i. For example, for a driver i selecting option A (i.e., with choice A), the choice-specific utility difference vector is

$$\boldsymbol{U}_i = \begin{bmatrix} V_{iB} - V_{iA} \\ V_{iM} - V_{iA} \end{bmatrix} = \boldsymbol{M_A} \begin{bmatrix} V_{iA} - V_{iM} \\ V_{iB} - V_{iM} \end{bmatrix} = \boldsymbol{M_A}\boldsymbol{U}_i^*. \tag{7}$$

In general, for a driver i with choice j, multiplying Eq. (5) by $\boldsymbol{M}_j$ leads to

$$\boldsymbol{U}_i = \boldsymbol{M}_j\boldsymbol{U}_i^* = \boldsymbol{M}_j\boldsymbol{\beta_0} + \boldsymbol{M}_j\boldsymbol{X}_i^*\boldsymbol{\beta} + \boldsymbol{M}_j\boldsymbol{\eta}_i^* = \tilde{\beta}_0 + \boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{\eta_i}, \tag{8}$$

where $\boldsymbol{\eta_i} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Omega}_j)$, $\boldsymbol{\Omega}_j = \boldsymbol{M}_j\boldsymbol{S}\boldsymbol{S}^T\boldsymbol{M}_j^T$, and $\tilde{\beta}_0 = \boldsymbol{M}_j\boldsymbol{\beta_0}$.

By proposing a choice-specific reformulation of the estimable model, the probability for driver i to choose option j can be formulated as

$$P_i(j) = \int_{-\infty}^{-\tilde{\beta}_{01} - \boldsymbol{X_{i1}}\boldsymbol{\beta}} \int_{-\infty}^{-\tilde{\beta}_{02} - \boldsymbol{X_{i2}}\boldsymbol{\beta}} n(\boldsymbol{\eta_i}, \boldsymbol{\Omega}_j)\, d\boldsymbol{\eta_i}, \tag{9}$$

[3] Additive redundancy means that by adding a positive constant a to each utility function defined in Eq. (3), drivers' choice probabilities remain unaffected. Thus, the constant a cannot be identified. Multiplicative redundancy means that by multiplying a positive constant c to each utility function defined in Eq. (3), drivers' choice probabilities remain unaffected. Thus, the constant c also cannot be identified.

where $n(\boldsymbol{\eta}_i, \boldsymbol{\Omega}_j)$ denotes the probability density function for a multivariate normal distribution with mean zero and covariance matrix $\boldsymbol{\Omega}_j$. Calculating the probability $P_i(j)$ is the key to estimating parameters, including multi-homing and switching costs, in the utility model. In this paper, we have a choice set $C = \{A, B, M\}$ with three options, and $P_i(j)$ which can be formulated as a double integral over normal random variables. Numerical integration is sufficient to solve this low-dimensional integral.

Next, we incorporate prior knowledge of the covariance matrix in our model to propose a Bayesian estimation framework.

4.4. Bayesian estimation

Let $\boldsymbol{\alpha}^T = [S_{21}, S_{22}]$ represent the vector containing parameters to be estimated in $\boldsymbol{S}$. Then the numerator of the joint posterior distribution can be written as

$$K(\boldsymbol{\alpha}, \boldsymbol{\beta} \mid \boldsymbol{X}_i, \boldsymbol{y}_i, \forall i = 1, \dots, n) \propto \prod_{i=1}^{n} \prod_{j \in C} [P_i(j)]^{y_{ij}} k(\boldsymbol{\alpha}) k(\boldsymbol{\beta}), \tag{10}$$

where

$$k(\boldsymbol{\alpha}) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{A}),\ k(\boldsymbol{\beta}) \sim \mathcal{U}(\boldsymbol{a}, \boldsymbol{b}). \tag{11}$$

$k(\boldsymbol{\alpha})$ and $k(\boldsymbol{\beta})$ are prior distributions for parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, respectively. $\boldsymbol{\mu}$ indicates the vector of means and $\boldsymbol{A}$ represents a diagonal covariance matrix. $\mathcal{U}(\boldsymbol{a}, \boldsymbol{b})$ denotes a multivariate uniform distribution with lower bound $\boldsymbol{a}$ and upper bound $\boldsymbol{b}$.

To draw samples from the joint posterior distribution, we use a Metropolis–Hastings (MH) algorithm, as described in Algorithm 1. The MH algorithm is an approach for obtaining a sequence of random samples from a multi-dimensional probability distribution. More detailed explanations of MH and other Markov chain Monte Carlo methods can be found in Train (2009), and practical guidance on implementing the MH algorithm is provided by Ellis (2018).

Algorithm 1 Metropolis–Hastings Sampler for Bayesian Estimation.

for τ in $1,\dots,T$ **do**
  Generate proposed parameters based on a jumping distribution q:
$$[\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*] \sim q\left([\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*] \mid [\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau]\right)$$
  Sample from a uniform distribution: $u \sim U(0, 1)$
  Calculate Hastings ratio:
$$H = \frac{K(\boldsymbol{\alpha}_*, \boldsymbol{\beta}_* \mid \boldsymbol{X}_i, \boldsymbol{y}_i, \forall i)}{K(\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau \mid \boldsymbol{X}_i, \boldsymbol{y}_i, \forall i)} \cdot \frac{q([\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau] \mid [\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*])}{q([\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*] \mid [\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau])}$$
  if $u < \min(1, H)$ **then**
    $[\boldsymbol{\alpha}_{\tau+1}, \boldsymbol{\beta}_{\tau+1}] = [\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*]$ ▷ Accept the proposed sample
  else
    $[\boldsymbol{\alpha}_{\tau+1}, \boldsymbol{\beta}_{\tau+1}] = [\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau]$ ▷ Reject the proposed sample
return Sequence of samples $\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau, \tau = 1,\dots,T$.

The jumping distribution used in Algorithm 1 is a multivariate normal distribution with a diagonal covariance matrix, i.e.,

$$q\left([\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*] \mid [\boldsymbol{\alpha}, \boldsymbol{\beta}]\right) = \mathcal{N}\left([\boldsymbol{\alpha}, \boldsymbol{\beta}], \begin{bmatrix} {\boldsymbol{\rho}_\alpha}^2 \boldsymbol{I} & \boldsymbol{0} \\ \boldsymbol{0} & {\boldsymbol{\rho}_\beta}^2 \boldsymbol{I} \end{bmatrix}\right), \tag{12}$$

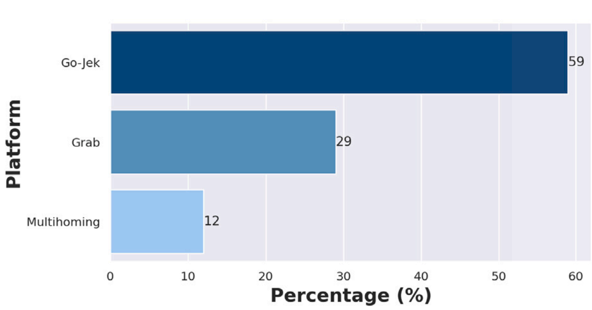
where $\boldsymbol{\rho}_\alpha$ and $\boldsymbol{\rho}_\beta$ are vectors of step sizes of the jumping distribution that need to be tuned during sampling to maintain a desirable acceptance rate (typically around 0.3). Since the jumping distribution q introduced here is a symmetric distribution, the ratio $\frac{q([\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau] | [\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*])}{q([\boldsymbol{\alpha}_*, \boldsymbol{\beta}_*] | [\boldsymbol{\alpha}_\tau, \boldsymbol{\beta}_\tau])}$ equals one when calculating the Hastings ratio in Algorithm 1.

T in Algorithm 1 is the number of iterations the MH sampler is conducted. In practice, we also introduce a burn-in stage with $\tilde{T}$ iterations at the beginning of the sampling process and a *thinning* procedure that reports samples every $\bar{\tau}$th iteration. The thinning process helps to mitigate the autocorrelation problem.

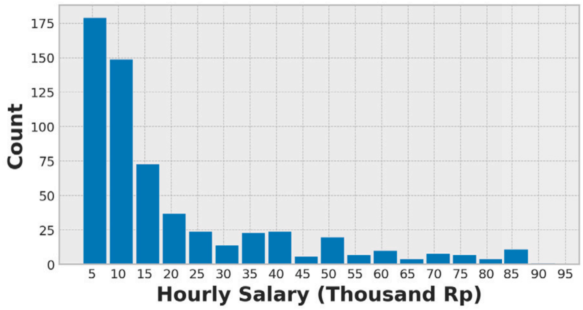
5. Data

To estimate multi-homing and switching costs using the framework proposed in Section 4, we collect self-reported payment and working hour data from a survey of platform drivers in Jakarta, Indonesia. The shared mobility market in Jakarta has two major platforms, Go-Jek and Grab. Go-Jek is an on-demand multi-service platform focusing on transportation services based in Indonesia, and Grab is a technology company that offers on-demand transportation, food delivery, and mobile payment services based in Singapore. Go-Jek operates in the Jakarta market first and Grab enters the market in 2014.

The survey was designed using an online survey platform Qualtrics and distributed to drivers through WhatsApp groups of Jakarta TNC drivers in March 2021. We estimate the proposed model in Section 4, in which Go-Jek is platform A and Grab is platform B. Survey questions are listed in Appendix B. $n = 846$ survey responses were collected from the ride-sourcing drivers who work for one or both of the platforms, and basic survey participants' statistics are shown in Appendix A.

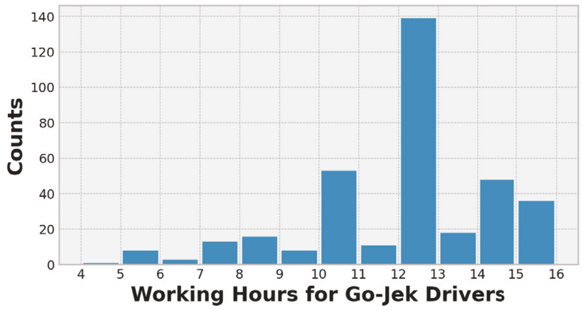


(a) Platform distribution of drivers.

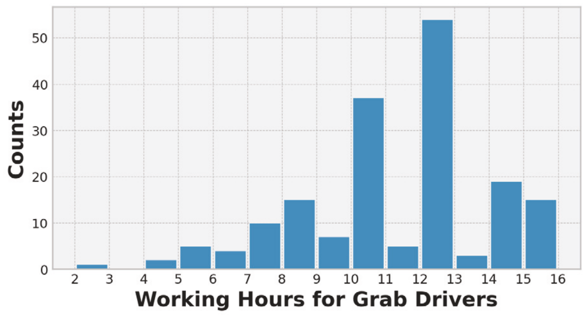


(b) Hourly salary of drivers.

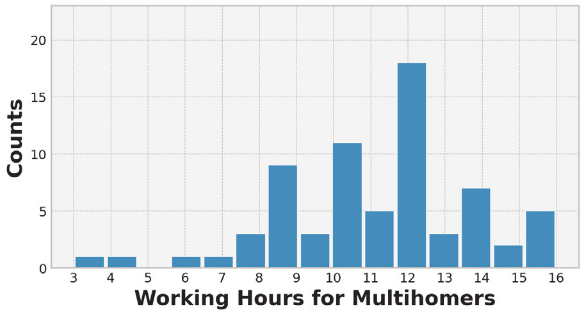
Fig. 1. Basic information of driver participants in the survey.



(a) Working hour distribution for Go-Jek drivers.



(b) Working hour distribution for Grab drivers.



(c) Working hour distribution for multihomers.

Fig. 2. Working hour distributions for the survey participants after filtering.

We preprocess driver responses according to three conditions: (i) the maximum reported daily working hours for any platforms should not exceed 16 h, (ii) the maximum hourly salary should not exceed 97,500 Rp (Salary Explorer, 2023), and (iii) the minimum hourly salary should be larger than 5 percentile among survey participants.[4] The data preprocessing results in 600 responses for our analysis. Fig. 1 shows the platform distribution and hourly salary distribution of driver data after performing data-cleaning steps. About 59% of drivers in our survey work exclusively for Go-Jek, compared with the 43% market share it had in Indonesia in March 2021 (Measureable AI, 2022). This means an oversampling of drivers on Go-Jek.

Fig. 2 shows the working hour distributions for Go-Jek-exclusive drivers, Grab-exclusive drivers, and multi-homers. For Go-Jek-exclusive drivers, most drivers work for 12 h per day, and the average daily working hours is 11.7. For Grab-exclusive drivers, most drivers work for 12 h per day, and the average daily working hours is 10.9. For multi-homing drivers, their working hours are reported in Fig. 2(c), with most multi-homers working for 12 h and average working hours of 11.2. In our survey, multi-homers could report working hours for both platforms if they work for Grab one day and Go-Jek the other day. Therefore, we calculate

[4] The inclusion of outliers leads to higher noise in our estimation.

Table 1
Summary of reasons for multi-homing.

Reasons for multi-homing	Agree	Disagree
Making more income	92.4%	7.6%
Serving more demand	88.6%	11.4%
Getting higher bonus	75.9%	24.1%
No multi-homing penalty	74.7%	25.3%

Table 2
Parameter values in the Bayesian estimation framework.

Parameter	Explanation	Value
$\bar{h}$	Maximum daily working hours	16
o	Hourly payment for outside options (in thousand Rp)	12.7
$\hat{a}$	Fixed scaling parameter in Bayesian estimation framework	408.646^2
T	Total iterations for the MCMC algorithm	100,000
$\tilde{T}$	Iterations for the burn-in stage	10,000
$\bar{\tau}$	Parameter for thinning procedure	10
m^{init}	Initial value for multi-homing cost (in thousand Rp)	100
s^{init}	Initial value for switching cost from Go-Jek to Grab (in thousand Rp)	100
$\bar{s}^{\text{init}}$	Initial value for switching cost from Grab to Go-Jek (in thousand Rp)	100
S_{21}^{init}	Initial value for parameter S_{21} in $\boldsymbol{S}$	408.646
S_{22}^{init}	Initial value for parameter S_{22} in $\boldsymbol{S}$	0
ρ_{α}	Step size vector for covariance vector $\boldsymbol{\alpha}$	$[0.7, 0.3]^T$
ρ_{β}	Step size vector for cost vector $\boldsymbol{\beta}$	$[15, 1.3, 0.1]^T$

working hours for multi-homers by taking an average between two platforms if the driver works more than 16 h for two platforms combined. The present method of calculating work hours for drivers who work for multiple ride-sourcing services may result in an underestimation of their total work hours. This could occur because some drivers may report their work hours for intra-day multi-homing strategies. However, given that multi-homers constitute only 12% of all drivers, this underestimation of work hours is likely to have a minimal impact on the estimation of multi-homing costs.

For driver participant i, we do not collect information about the initial working platform j_i. In the model estimation, we assume that drivers are initially randomly matched to a platform with a probability given by the market share of the companies at the time of our study (43% Go-Jek *vs.* 57% Grab in March 2021 when the survey was distributed Measureable AI, 2022). Our results are robust to other probabilities of random matching based on experimental results.

In addition, the survey elicited reasons for why multi-homing drivers choose to multi-home. Table 1 shows a brief summary of survey results. Among all four listed reasons, the top reasons for drivers to multi-home are making more money and having more demand to serve. Platform bonuses and penalties for working for another platform are less important for multi-homing decisions.

In the next section, we present estimation results. We emphasize that while the analysis is performed for the Jakarta TNC duopoly, the model is also applicable to any entry into other monopolistic TNC markets.

6. Results

Parameter values used in the estimation are shown in Table 2. To estimate the multi-homing and switching costs in the Jakarta ride-sourcing market, we first estimate payment functions for Go-Jek and Grab with respect to working hours (i.e., functions $P_A(h_A)$ and $P_B(h_B)$ in the model). The maximum daily working hours each day are set to 16 h, i.e., $\bar{h} = 16$.

We assume that the payment functions of both platforms follow a constant wage elasticity functional form $y = ax^b$, where x indicates the number of working hours, y denotes total earnings, and a and b are parameters. The assumption of a constant wage elasticity for day/night/other shifts is made in studies such as Farber (2015) (refer to Fig. 4 in that study) as an example. Fig. 3 shows the estimated payment functions for both Go-Jek and Grab. All units of earnings are in thousand rupiahs (Rp). Our point estimates are:

$$y_{\text{Go-Jek}} = 62.318 \times x_{\text{Go-Jek}}^{0.496},$$
$$y_{\text{Grab}} = 43.298 \times x_{\text{Grab}}^{0.786}.$$

Parameter b in the proposed payment function corresponds to a marginal payment multiplier. The estimated functions depicted in Fig. 3 indicate that Grab has a higher marginal payment multiplier than Go-Jek. However, Go-Jek pays higher when working fewer hours (less than 3 h) than Grab.

Next, we estimate the variances for hourly payments of Jakarta ride-sourcing drivers. The estimated variance combining Grab and Go-Jek data for hourly payments is 326.155 thousand Rp. Assume that each driver has an outside option that provides them with a Jakarta provincial minimum wage (Chau, 2021) and the average hourly salary for outside options is approximated as $o = 12.7$ thousand Rp.

Given payment functions for both platforms and the hourly salary for outside options, we calculate the optimal working hour allocations for drivers who work exclusively for Go-Jek (i.e., Option A), work exclusively for Grab (i.e., Option B), and multi-home

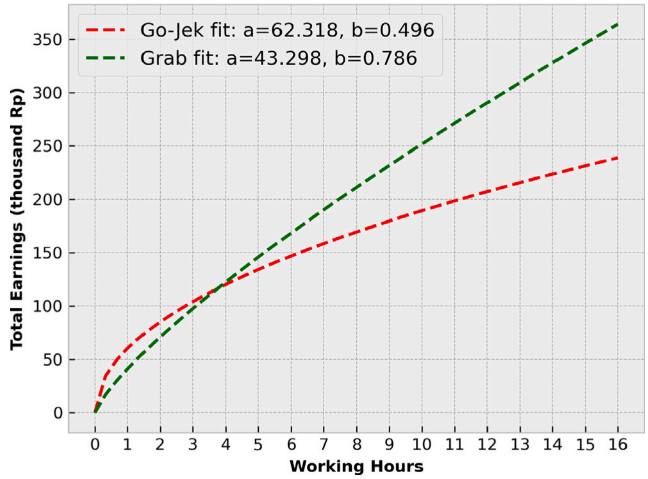
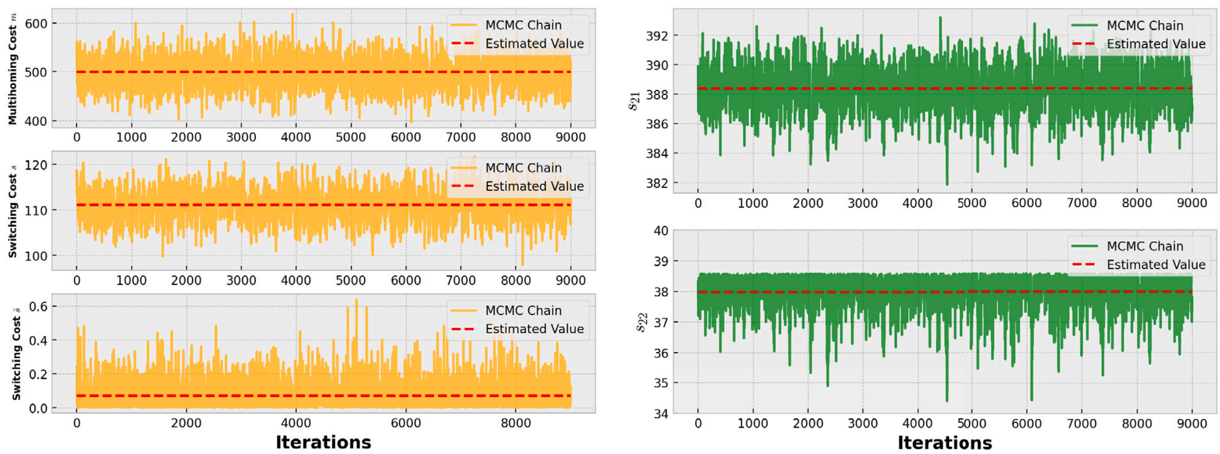


Fig. 3. Fitted payment functions for Go-Jek and Grab.



(a) Cost parameters m, s, and $\tilde{s}$.

(b) Covariance parameters S_{21} and S_{22}.

Fig. 4. Samples drawn from the Bayesian estimation framework given one initial platform allocation.

on both platforms (i.e., Option M) based on the fixed utility formula in Eq. (3). Since our survey data only collect drivers' current working-hour allocations, a counterfactual assumption on drivers' working-hour allocations for the two other options is necessary to estimate multi-homing and switching costs. In our estimation, we assume that, counterfactually, drivers allocate their working hours optimally. That is, a driver's choice to not multi-home requires their non-multi-homing utility to be higher than the highest utility they can achieve from multi-homing. For example, when maximizing fixed utilities (earnings), drivers who work exclusively for Go-Jek should work 5.8 h per day on the ride-sourcing platform. Drivers who switch to Grab should work 16 h per day on providing ride-sourcing services. When maximizing fixed earnings, Grab drivers should work significantly more hours on the ride-sourcing platform compared to Go-Jek drivers, since Grab offers higher competitive earnings. It is consistent with the implication in Eq. (3). Multihomer should allocate 2.5 h per day to Go-Jek and 13.5 h per day to Grab.

We use the Bayesian framework proposed above to estimate multi-homing and switching costs. We use an uninformative prior for the cost vector,

$$k(\boldsymbol{\beta}) \sim \mathcal{U}(\mathbf{0}, \mathbf{10000}).$$

For $\boldsymbol{\alpha}$, we use an uninformative prior as well,

$$k(\boldsymbol{\alpha}) = k\left(\begin{bmatrix} S_{21} \\ S_{22} \end{bmatrix}\right) \sim \mathcal{N}\left(\begin{bmatrix} 408.646 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right).$$

The fixed scaling factor $\hat{a}$ in the covariance matrix $\boldsymbol{\Omega}^*$ is set to be $\hat{a} = \omega^*_{11} = 408.646^2$. The prior distributions and the scaling factor are chosen based on the following steps.

Table 3
Estimation results. Average estimated values across 10 different initial platform allocations are reported. SD indicates the standard deviation of estimated values across 10 runs. 95% CI represents the 95% confidence interval, which is the union of 95% CIs among 10 runs.

Parameter (Unit)	Mean	SD	95% CI
m (thousand Rp)	496.271	2.468	[444.090, 549.317]
s (thousand Rp)	111.64	3.795	[102.741, 126.124]
$\tilde{s}$ (thousand Rp)	0.069	0.001	[0.003, 0.218]
S_{21} (thousand Rp)	388.156	0.612	[384.940, 391.800]
S_{22} (thousand Rp)	37.950	0.047	[36.507, 38.549]
log-likelihood	−1695.337	25.126	

The prior distribution is selected to best fit the covariance matrix $\boldsymbol{\Omega}^*$. Assume that hourly payment for Go-Jek, Grab, and outside options have identical and independent errors, the variances for $\epsilon_{iA}, \epsilon_{iB}$, and ϵ_{iM} should be equal to 16^2 (working 16 h per day) times the variance of hourly payment (326.155 estimated from the data), i.e.,

$$\mathrm{var}(\epsilon_{iA}) = \mathrm{var}(\epsilon_{iB}) = \mathrm{var}(\epsilon_{iM}) = \mathrm{var}(\epsilon_i) = 16^2 \times 326.155 = 83495.68.$$

The error vector $\boldsymbol{\eta}_i^*$ is constructed by subtracting error terms $\epsilon_{iA}, \epsilon_{iB}$, and ϵ_{iM}. Therefore, we can approximate the variances for $\boldsymbol{\eta}_i^*$ (assuming independence between error terms) as

$$\mathrm{var}(\eta_{i1}^*) = \mathrm{var}(\eta_{i2}^*) = 2 \times \mathrm{var}(\epsilon_i) = 166991.36 = 408.646^2.$$

Meanwhile, η_{i1}^* and η_{i2}^* should be positively correlated and the correlation coefficient should be close to one, i.e.,

$$\frac{\mathrm{cov}(\eta_{i1}^*, \eta_{i2}^*)}{\sqrt{\mathrm{var}(\eta_{i1}^*) \cdot \mathrm{var}(\eta_{i2}^*)}} \longrightarrow 1.$$

For the covariance matrix $\boldsymbol{\Omega}^*$, we have

$$\boldsymbol{\Omega}^* = \boldsymbol{S}\boldsymbol{S}^T = \begin{bmatrix} \sqrt{\hat{a}} & 0 \\ S_{21} & S_{22} \end{bmatrix} \cdot \begin{bmatrix} \sqrt{\hat{a}} & S_{21} \\ 0 & S_{22} \end{bmatrix} = \begin{bmatrix} \hat{a} & \sqrt{\hat{a}}S_{21} \\ \sqrt{\hat{a}}S_{21} & S_{21}^2 + S_{22}^2 \end{bmatrix}.$$

Therefore, we have the following system of equations:

$$\hat{a} = 408.646^2;\ S_{21}^2 + S_{22}^2 = 408.646^2;\ \frac{\sqrt{\hat{a}}S_{21}}{\sqrt{\hat{a}}\sqrt{S_{21}^2 + S_{22}^2}} = 1.$$

Solutions to the system of equations are $S_{21} = 408.646$ and $S_{22} = 0$. For prior distributions of parameters S_{21} and S_{22}, we use normal distributions with variances equal to one around the values we calculated.

For the MCMC algorithm, we set the burn-in stage to $\tilde{T} = 10{,}000$ iterations and a thinning procedure with $\bar{\tau} = 10$. The total number of iterations is set to $T = 100{,}000$. We calculate the final estimates from 9,000 samples.

In our numerical experiments, we generated the initial platform allocations for drivers randomly, with sampling probabilities given by the market shares of Grab and Gojek in the TNC driver labor market. To ensure the robustness of our findings, we repeated the initial platform allocation process 10 times and calculated the average values, which we then adopted as our final estimation results.

Initial values for the estimation are $m^{\text{init}} = 100$, $s^{\text{init}} = 100$, $\tilde{s}^{\text{init}} = 100$, $S_{21}^{\text{init}} = 18.639$, and $S_{22}^{\text{init}} = 0$. The step size for proposing functions are set to $\boldsymbol{\rho}_{\beta} = [15, 1.3, 0.1]^T$ and $\boldsymbol{\rho}_{\alpha} = [0.7, 0.3]^T$, which leads to an average acceptance rate around 28%. The sampled values of parameters for one estimation run are shown in Fig. 4, and estimated values for parameters are shown in Table 3.

The results of our estimation reveal that there is a high cost associated with multi-homing and switching from Go-Jek to Grab, but a low cost for switching from Grab to Go-Jek. The low standard deviations indicate that the initial platform allocations have a limited impact on the parameter estimations. As seen in Fig. 3, the payment functions suggest that Grab pays more than Go-Jek, but there is a greater number of drivers working for Go-Jek rather than multi-homing or working for Grab. These observations are in line with the substantial costs of multi-homing and one-way switching (from Go-Jek to Grab) in the Jakarta TNC duopoly.

The interpretation of switching and multi-homing costs differ, given our characterization in Section 3. Whereas multi-homing cost is mostly a daily cost, switching costs are perceived once. To get a sense of the one-cost equivalent of the switching cost, consider an agent that expects to stay another two years on a platform, with a discount factor of 6.1% per annum (see Zhuang et al. (2007) for a review and estimation of discount rates in different countries); 6.1% is an estimated discount rate for Indonesia. The one-time equivalent of the switching cost from Go-Jek to Grab is

$$s \times \frac{1 - 1.061^{-(365\times2)/365}}{1 - 1.061^{-1/365}} = 111.64 \times \frac{1 - 1.061^{-2}}{1 - 1.061^{-1/365}} \approx 76{,}862,$$

which is significant (approximately USD 5,000). It should be mentioned that we have conducted a back-of-the-envelope estimation for the one-time switching expense, assuming that drivers remain in the ride-sourcing market for two years. As the perceived cost of

Table 4
Estimation results in a simplified model.

Parameter (Unit)	Mean	SD	95% CI
m (thousand Rp)	459.574	2.847	[456.928, 465.741]
s (thousand Rp)	113.062	2.360	[110.882, 119.144]
$\tilde{s}$ (thousand Rp)	0.065	0.001	[0.064, 0.067]
S_{21} (thousand Rp)	378.773	1.152	[376.779, 380.227]
S_{22} (thousand Rp)	−25.140	1.620	[−27.470, −22.210]
log-likelihood	−1940.629	33.923	

switching surfaces daily during this two-year period, the cumulative expense becomes substantial. However, given that ride-sourcing drivers in Jakarta may work for a shorter duration before transitioning to other employment opportunities, the one-time switching expense may be lower. Nevertheless, the simplified calculation underscores the importance of the switching cost in the ride-sourcing market.

6.1. Robustness in optimal working hour choice

We note that an assumption for this model is that drivers make optimal working-hour allocations that maximize the fixed utility in Eq. (3) for options other than their observed (reported) ones. However, drivers' reported working-hour allocations for their current choices might not be optimal for several reasons: Drivers do not have complete information on platforms' payment functions or drivers simply do not maximize their earnings. To ensure the consistency of working-hour allocation across different options for drivers, we propose a simplified estimation model that assumes drivers always choose the optimal working-hour allocation for each option. The simplified model only uses reported platform choices from drivers and computes the optimal working hours using fixed utility parts of Eq. (3). Table 4 shows estimation results for the simplified model.

It is to be expected that using fewer data results in an estimated model with a lower likelihood. The values of the estimated parameters show a significant decrease in the multi-homing cost, while the two switching costs remain largely unchanged compared to the baseline estimation results. For drivers, working on multiple platforms is more profitable than just one. Go-Jek offers higher pay during the first three hours, while Grab provides more earnings for those who work more hours. When drivers optimize their work to maximize their earnings, the earning differences between multihoming and working for a single platform become tighter, and market frictions become less significant.

6.2. Robustness in initial platform allocation

The model estimation assumes that drivers' initial platform allocations align with the currently observed market share. However, it is certainly possible that drivers have varying initial platform distributions. To assess the robustness of this assumption, we estimate multi-homing and switching costs under 11 different scenarios, with the proportion of drivers who initially work for Go-Jek ranging from 0% to 100%. The results are displayed in Table 5.

When having 0% drivers initially working for Go-Jek, switching cost from Go-Jek to Grab s cannot be estimated as s is not involved in the likelihood function. Similar to switching cost from Grab to Go-Jek $\tilde{s}$ when having 100% drivers initially working for Go-Jek. When increasing the percentage of drivers who initially work for Go-Jek, the multi-homing cost m increases. The switching cost from Grab to Go-Jek $\tilde{s}$ is close to 0 in all scenarios. The low values of standard deviation indicate that the randomization of initial working platforms for individual drivers does not have a large impact on the estimation results.

The robustness analysis shows that the estimated multi-homing costs fall between 368.296 and 579.888, while the estimated cost of switching from Go-Jek to Grab is estimated to be between 101.977 and 112.763. Meanwhile, the cost of switching from Grab to Go-Jek is estimated to be between 0.05 and 0.223. Despite the uncertainty of the real initial platform allocation of drivers, the magnitude of the estimated costs remains unchanged. For the purpose of our counterfactual analysis, we have selected a set of estimated values for multi-homing and switching costs from within the given range (as presented in Table below).

7. Counterfactual predictions

In this section, we conduct a set of sensitivity and counterfactual analyses on multi-homing and switching costs over market share and drivers' welfare based on the baseline estimation results in Table 3.

Table 6 reports sensitivity and counterfactual analysis results. For marginal changes in switching and multi-homing costs, market shares, the fraction of multi-homing drivers, and drivers' expected utility are reported. The results of the sensitivity analysis for the switching cost from Grab to Go-Jek, represented by $\tilde{s}$, are not presented in this section as the value of $\tilde{s}$ is minimal and its alteration has no impact on the market shares. The average utility is calculated by taking the expectation of utility for each option under optimal working-hour allocation.

First, consider the multi-homing costs. Decreases by 1% lead to a 2.1% increase in the number of multi-homing drivers. Average driving utility, surprisingly, is monotonic in multi-homing cost. Hence, making multi-homing easier negatively impacts drivers. This is a result of the high level of multi-homing and switching costs.

Table 5
Estimation results given different proportions of drivers who initially work for Go-Jek.

Initial Go-Jek percentage	m	s	$\tilde{s}$	SD(m)	SD(s)	SD($\tilde{s}$)
0%	368.296	–	0.050	–	–	–
10%	405.160	101.977	0.053	3.282	10.951	0.001
20%	435.962	106.493	0.057	3.510	6.695	0.001
30%	464.316	110.004	0.061	3.483	4.274	0.001
40%	488.029	110.727	0.066	3.088	3.867	0.001
50%	510.573	111.278	0.074	3.441	3.951	0.001
60%	532.677	112.642	0.086	2.959	3.392	0.003
70%	551.238	112.713	0.103	1.694	1.717	0.003
80%	564.592	112.763	0.137	1.336	1.120	0.005
90%	574.579	111.909	0.223	0.882	0.764	0.014
100%	579.888	110.653	–	–	–	–

Table 6
Sensitivity and counterfactual analyses results. The percentage in parentheses represents relative changes compared with baseline percentages.

Cost change	Go-Jek exclusive	Grab exclusive	Multihomer	Average utility
Baseline	9.56%	77.82%	12.62%	273.127
$m + 1\%$	9.57% (+0.07%)	78.08% (+0.33%)	0.12% (−2.07%)	273.676 (+0.20%)
$m - 1\%$	9.55% (−0.08%)	77.57% (−0.33%)	0.13% (+2.10%)	272.588 (−0.20%)
$s + 1\%$	9.75% (+1.96%)	77.64% (−0.24%)	0.13% (−0.01%)	272.593 (−0.20%)
$s - 1\%$	9.37% (−1.93%)	78.01% (+0.24%)	0.13% (+0.01%)	273.662 (+0.20%)

Table 7
Sensitivity and counterfactual analyses results for payment function parameters regarding labor supply of Go-Jek, Grab, and the overall shared mobility market. $a_{\text{Go-Jek}}$ and $b_{\text{Go-Jek}}$ are parameters for Go-Jek's payment function, a_{Grab} and b_{Grab} are parameters for Grab's payment function, and o stands for hourly pay for the outside option. The percentage in parentheses represents relative changes compared with the labor supply in the baseline scenario.

	Payment change	$a_{\text{Go-Jek}}$	$b_{\text{Go-Jek}}$	a_{Grab}	b_{Grab}	o
Go-Jek supply	Baseline	0.87				
	Increase 1%	0.89 (+2.30%)	0.90 (+3.45%)	0.78 (−10.34%)	0.68 (−21.84%)	0.86 (−1.15%)
	Decrease 1%	0.85 (−2.30%)	0.84 (−3.45%)	0.97 (+11.49%)	1.10 (+26.44%)	0.88 (+1.15%)
Grab supply	Baseline	14.16				
	Increase 1%	14.15 (−0.07%)	14.15 (−0.07%)	14.39 (+1.62%)	14.63 (+3.32%)	14.16 (+0.00%)
	Decrease 1%	14.16 (+0.00%)	14.17 (+0.07%)	13.90 (−1.84%)	13.56 (−4.24%)	14.16 (+0.00%)
Total supply	Baseline	15.03				
	Increase 1%	15.04 (+0.07%)	15.05 (+0.13%)	15.17 (+0.93%)	15.32 (+1.93%)	15.01 (−0.13%)
	Decrease 1%	15.01 (−0.13%)	15.01 (−0.13%)	14.87 (−1.06%)	14.66 (−2.46%)	15.04 (+0.07%)

For switching cost from Go-Jek to Grab, decreasing it by 1% leads to 1.93% fewer Go-Jek-exclusive drivers, 0.01% more multi-homing drivers, and a 0.24% increase in Grab-exclusive drivers compared with the baseline scenario. Average driver utility increases when the switching cost decreases. For the current ride-sourcing market in Jakarta, reducing switching costs brings higher utility to drivers on average.

Last, consider the amount of driver labor supply when varying switching and multi-homing cost. As in the rest of the analysis, we assume that drivers will allocate their working hours optimally conditional on their multi-homing or single-homing choice. Changes in optimal working-hour allocations lead to changes in the probability that drivers choose to single- or multi-home. We determine the average labor supply to each platform by combining working-hour allocations and drivers' choice probabilities. Table 7 shows the sensitivity and counterfactual analyses for parameters in payment functions. It is worth noting that 1% change in parameter a leads to 1% change in drivers' wage. Therefore, sensitivity analyses with parameters $a_{\text{Go-Jek}}$ and a_{Grab} correspond to the labor supply elasticity in the duopoly competing markets.

For Go-Jek, increasing its wage by 1% (the scenario in which $a_{\text{Go-Jek}}$ increases by 1%) leads to a 2.3% increase in its driver supply; decreasing Go-Jek wage by 1% (the scenario in which $a_{\text{Go-Jek}}$ decreases by 1%) leads to a 2.3% decrease in its driver supply. For Grab, increasing its wage by 1% (the scenario in which a_{Grab} increases by 1%) leads to a 1.62% increase in its driver supply; decreasing Grab wage by 1% (the scenario in which a_{Grab} decreases by 1%) leads to a 1.84% decrease in its driver supply. Note that the structure of our model implies positive labor supply elasticities. As expected in a competitive market, driver labor supply elasticities with respect to platform wage (i.e., driver payment) are significantly higher than those observed in monopoly markets (e.g., Sun et al. (2019)).

With respect to the impact of driver payment over the competitive platform, increasing Go-Jek wage by 1% leads to a 0.07% decrease in Grab's driver supply; decreasing Go-Jek wage by 1% leads to a marginal increase in Grab's driver supply as Go-Jek has much fewer supply than Grab. For Grab, increasing its wage by 1% leads to a 10.34% decrease in Go-Jek's driver supply; decreasing Grab's wage by 1% leads to an 11.49% increase in Go-Jek's driver supply. The fact that cross-elasticities are negative is a property

Table 8
Sensitivity and counterfactual analyses results for payment function parameters regarding labor supply of Go-Jek, Grab, and the overall shared mobility market assuming a reduced multi-homing cost (90% of the estimated multi-homing cost).

	Payment change	$a_{\text{Go-Jek}}$	$b_{\text{Go-Jek}}$	a_{Grab}	b_{Grab}	o
Go-Jek supply	Baseline	0.94				
	Increase 1%	0.95 (+1.06%)	0.97 (+3.19%)	0.85 (−9.57%)	0.75 (−20.21%)	0.92 (−2.13%)
	Decrease 1%	0.92 (−2.13%)	0.90 (−4.26%)	1.03 (+9.57%)	1.16 (+23.40%)	0.95 (+1.06%)
Grab supply	Baseline	14.10				
	Increase 1%	14.09 (−0.07%)	14.09 (−0.07%)	14.33 (+1.63%)	14.58 (+3.40%)	14.1 (+0.00%)
	Decrease 1%	14.11 (+0.07%)	14.11 (+0.07%)	13.84 (−1.84%)	13.51 (−4.18%)	14.10 (+0.00%)
Total supply	Baseline	15.04				
	Increase 1%	15.05 (+0.13%)	15.06 (+0.20%)	15.17 (+0.93%)	15.32 (+1.93%)	15.02 (−0.07%)
	Decrease 1%	15.02 (−0.07%)	15.02 (−0.07%)	14.88 (−1.00%)	14.67 (−2.40%)	15.05 (+0.13%)

Table 9
Sensitivity and counterfactual analyses results for payment function parameters regarding labor supply of Go-Jek, Grab, and the overall shared mobility market assuming a reduced switching cost from Go-Jek to Grab s (90% of the estimated switching cost).

	Payment change	$a_{\text{Go-Jek}}$	$b_{\text{Go-Jek}}$	a_{Grab}	b_{Grab}	o
Go-Jek supply	Baseline	0.77				
	Increase 1%	0.78 (+1.30%)	0.79 (+2.60%)	0.69 (−10.39%)	0.61 (−20.78%)	0.76 (−1.30%)
	Decrease 1%	0.75 (−2.60%)	0.74 (−3.90%)	0.85 (+10.39%)	0.97 (+25.97%)	0.78 (+1.30%)
Grab supply	Baseline	14.43				
	Increase 1%	14.43 (+0.00%)	14.43 (+0.00%)	14.63 (+1.39%)	14.84 (+2.84%)	14.43 (+0.00%)
	Decrease 1%	14.44 (+0.07%)	14.44 (+0.07%)	14.21 (−1.52%)	13.91 (−3.60%)	14.43 (+0.00%)
Total supply	Baseline	15.20				
	Increase 1%	15.21 (+0.07%)	15.22 (+0.13%)	15.32 (+0.79%)	15.45 (+1.64%)	15.19 (−0.07%)
	Decrease 1%	15.19 (−0.07%)	15.19 (−0.07%)	15.06 (−0.92%)	14.88 (−2.11%)	15.21 (+0.07%)

of the model. Note the much higher cross-price elasticities for Grab than for Go-Jek, which points to the fact that market frictions restrict Go-Jek less in its pricing than Grab.

Wage changes for drivers on Go-Jek have a small and positive impact on the total driver supply. Specifically, increasing Go-Jek wage by 1% leads to a 0.07% decrease in total driver supply. On the other hand, wage changes for drivers on Grab have a more profound impact on the total driver supply. Specifically, increasing Grab wage by 1% leads to a 0.93% increase in total driver supply; decreasing Grab wage by 1% leads to a 1.06% decrease in total driver supply.

In regards to the hourly rate for outside options, a hike in this value results in a reduction in labor supply in the Jakarta shared mobility sector. When the payment for outside options is increased (such as a 1% rise in o), the Go-Jek driver supply decreases accordingly (for instance, by 1.15%). This is because Go-Jek drivers tend to spend more time working for outside options. On the other hand, an increase in the payment for outside options has no effect on Grab driver supply, as the earning potential through Grab is more favorable than outside options. Currently, Grab drivers opt to provide ride-hailing services for the maximum number of hours, i.e., 16, in order to maximize their earnings.

As the prior analysis showed, reducing multi-homing and switching costs have different impacts on driver welfare. As a last counterfactual, we consider elasticities with respect to payment parameters under reduced multi-homing cost and the switching cost from Go-Jek to Grab.

Table 8 shows the sensitivity and counterfactual analyses with payment function parameters assuming a reduced multi-homing cost, which is 90% of the estimated multi-homing cost. Comparing results from Tables 7 and 8, we find that labor supply elasticity on its own platform, competitive platform, and the total supply decreases given a reduced multi-homing cost. Also, the total labor supply in the shared mobility market has a marginal increase when reducing the multi-homing costs for drivers. Reducing the multi-homing cost leads to more Go-Jek supply and less Grab supply. This is intuitive; with a lower multi-homing cost for drivers, more drivers will switch from Grab-exclusive to multi-homing and allocate some working hours to Go-Jek, as Go-Jek provides higher earnings at the first several hours.

Table 9 displays the sensitivity and counterfactual analyses with payment function parameters given a reduced switching cost from Go-Jek to Grab s, which is 90% of the estimated switching cost s. Compared to reducing multi-homing costs, reducing switching cost s have a larger impact on the total labor supply, where the total labor supply increases by 1.13%. The labor supply for Go-Jek decreases while the labor supply for Grab increases since more drivers switch to work exclusively for Grab as the switching cost decreases.

The comparison results imply that ignoring multi-homing and switching costs might lead to biased labor supply elasticity estimates, and mislead decision-making. Therefore, it is crucial to consider both switching and multi-homing costs in the modeling and analysis of shared mobility markets.

8. Conclusion and future work

In this paper, we examine the multi-homing and switching behavior of freelance drivers in shared mobility markets. We taxonomize frictions using notions from consumer purchase decisions. We propose a structural model of driver labor supply on platforms when they face switching and multi-homing costs. And we empirically estimate these costs using public and survey data in a shared mobility platform duopoly. We find that the estimated multi-homing and switching costs are substantial, and interventions to reduce these costs have significant and economically relevant effects on market shares and driver welfare.

The analysis has several limitations. First, in both the estimations of the working hour choice, bias may arise from self-selection and omitted variables. There are omitted variables biasing the estimation of the payment functions: Drivers that have unobserved characteristics that make them more productive on a platform will work more hours there, leading us to overestimate payments. Similarly, the assumption of random matching might be improved: Drivers would choose to start working for a platform that they expect, given their unobserved characteristics, to gain the highest payments on. This selection effect bias estimates for payments by both platforms. Second, we assume drivers make optimal working hour allocations for working options that are not reported. This assumption leads to inaccurate estimations of both multi-homing and switching costs. Third, multi-homers' strategies (interday or intraday multi-homing) are unknown, which leads to inaccurate working hours and earnings for multi-homers. Finally, drivers are assumed to have identical maximum working hours, which could vary across different drivers. The model can produce estimated results more accurately by collecting more detailed information from a targeted group of drivers and considering drivers' heterogeneity.

We propose two avenues for future research.

Platform competition with market frictions: A first avenue is to better understand platform competition and market efficiency of shared mobility markets in the presence of switching and multi-homing costs, as well as platform integration. For example, we observed an asymmetry in the effectiveness of reducing multi-homing and switching costs in increasing driver utility. Research investigating platform competition and market structure and the interaction of market frictions in shared mobility markets would improve our understanding of the duopoly market—and how to regulate it (e.g., Yu et al. (2020) and Li et al. (2022)).

Empirical strategies: While our study uses limited data to obtain estimates, we pointed out several ways to improve our estimation strategy. Additional exogenous variations, such as one resulting from regulatory changes, may give additional avenues to credibly identify parameters in the model proposed. Additionally, we view the wage functions as exogenous, which might not approximate reality well. We also do not consider driver heterogeneity. A more detailed survey could elicit additional control variables and decrease confounding.

CRediT authorship contribution statement

Xiaotong Guo: Conceptualization, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Andreas Haupt:** Conceptualization, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Hai Wang:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Supervision, Resources, Methodology, Validation, Writing – review & editing. **Rida Qadri:** Data curation, Visualization. **Jinhua Zhao:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

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Appendix A. Survey participants basic statistics

The basic statistics (age, gender and education level) of survey participants are shown in Figs A.5, A.6, and A.7. Most survey participants are male with high school degrees and have ranged in age from 30 to 39.

Appendix B. Online survey questions

The survey consists of four questions blocks:

- A first block elicits information relating to driving beyond particular TNCs. Respondents first report all TNCs they have worked for in the last 30 days. We treat respondents as multi-homers if they have worked for at least two platforms in the past 30 days. Then, respondents report driving behavior and other driving-related information, e.g., the vehicle type used, previous occupation, and behaviors while waiting for the next ride.
- A second block separates multi-homers from non-multi-homers. Multi-homers are asked how they switch between different platforms, how they allocate their working hours, and reasons for their multi-homing. Non-multi-homers report reasons for non-multihoming and factors that would make them multi-home.
- In the third block, for all ride-sourcing platform survey participants who have worked in the last 30 days, we asked a number of questions about driving activities during the last two weeks. These questions included whether drivers mostly worked on delivering food or transporting passengers, their most frequent driving area, days and hours to work, total driving distance, and daily salaries.
- A final block elicited socio-demographic characteristics including age, gender, educational status, income level, living areas, and weekly expenses.

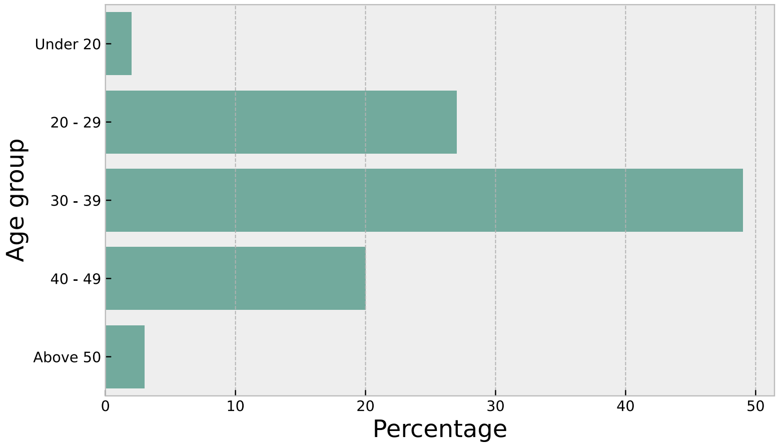

Fig. A.5. Age distributions for survey participants.

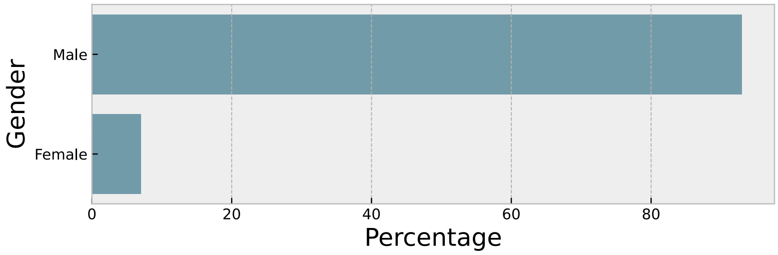

Fig. A.6. Gender distributions for survey participants.

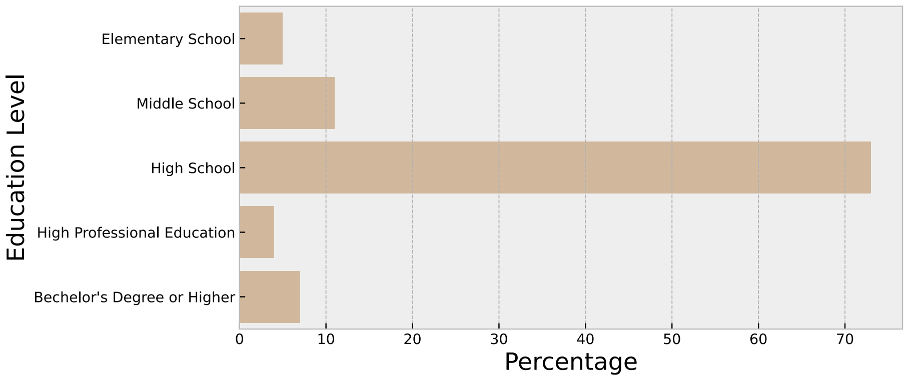

Fig. A.7. Education level distributions for survey participants.

B.1. Basic driving information and behavior

1. Which ride-hailing platform companies did you work for in the last 30 days? (Select all that apply)
   (a) Grab (b) Go-Jek (c) Shopee
2. What type of vehicle do you use the most for work?
   (a) Car (b) Motorbike
3. How did you acquire this vehicle?

   (a) I or a family member purchased it with full payment
   (b) I or a family member purchased it on credit
   (c) I leased it through the ride-hailing platform
   (d) I leased it myself through a third party

(e) Others (please specify)

4. Did you drive for a taxi company in the last 30 days, e.g. for bluebird?
   (a) Yes (b) No
5. Did you work in any other jobs in addition to either ride-hailing and/or taxi driving in the last 30 days?
   (a) Yes (please specify job type) (b) No
6. Did this job give you more money per hour than money for an hour you are on the bid?
   (a) Yes (b) No
7. Do you like this job more or less than working for Grab/Go-Jek/Shopee?
   (a) Yes (b) No (c) Indifferent
8. What job did you have before starting as an ojol?
   (a) Opang (b) Other (c) Ojol is my first job
9. Did this job give you more money per hour than money for an hour you are on the bid?
   (a) Yes (b) No
10. Why did you change jobs? (Select all that apply)
    (a) Better pay
    (b) Lost my previous job
    (c) More flexible hours
    (d) My friends were joining ojol
    (e) I like this job better
    (f) More respected/higher status as an ojol
    (g) Other (Please specify)
11. Where do you prefer to wait when not on an order (most frequently)?
    (a) Wait in the area where last ride/order ended
    (b) Drive to nearest hangout/resting spots with other drivers
    (c) Driver to high demand areas even if I have to drive there
    (d) Others (please specify)
12. When do you usually stop working (most frequently)?
    (a) When I reach a certain income
    (b) When I get enough points/tupo
    (c) At a set time I set for myself
    (d) When I get tired
    (e) Others (please specify)

B.2. Multi-homing behavior

B.2.1. For non-multihomers

13. Why do you not use multiple platforms and only use one platform? Check whether you agree with the following statements.
    (a) I have enough work on one so do not need to work for both (Disagree/Agree)
    (b) I fear retaliation by the platform (Disagree/Agree)
    (c) I understand one system much better than the other (Disagree/Agree)
    (d) I feel loyal to my platform (Disagree/Agree)
    (e) I want to maintain my ranking on one of the platforms (Disagree/Agree)
    (f) I don’t like the other platform (Disagree/Agree)
    (g) My friends/community are on this platform (Disagree/Agree)
    (h) I want to concentrate/focus on one platform for better performance (Disagree/Agree)
14. Would the following factors be important in your decision to start working for multiple platforms at the same time?
    (a) Higher bonus on the other platform (Yes/No)
    (b) Higher income on the other platform (Yes/No)
    (c) No penalty for multihoming (Yes/No)
    (d) My friends/community began to multihome (Yes/No)
    (e) More orders/demand on the other platform (Yes/No)
    (f) Understanding the other system better (Yes/No)
15. If you were to leave your current platform and ONLY WORK for the other platform, would the following factors be important in the decision to switch?

(a) Higher bonus on the other platform (Yes/No)
(b) Higher Income on the other platform (Yes/No)
(c) More orders/demand on the other platform (Yes/No)
(d) All your friends/community shifting to the other platform (Yes/No)
(e) Understanding the other system better (Yes/No)
(f) None of these will make me change to the other platform and leave my current application (Yes/No)

16. Anything else we should know about why you decided to not use multiple platforms?

B.2.2. For multihomers

17. How do you usually switch between multiple companies?

(a) Have multiple phones open at the same time
(b) I block times, i.e. have one company open on my phone for each time period
(c) Have multiple apps running on the same phone throughout the day
(d) Only check the other company when I don't get orders for some time
(e) Others (please specify)

18. What percentage of your working day do you have multiple phones open at the same time? (0–100)
19. Were the following factors important in your decision to start working for multiple platforms?

(a) Getting a higher bonus on one of the platforms (Yes/No)
(b) Making more income on one of the platforms (Yes/No)
(c) Knowing there is no penalty for multihoming (Yes/No)
(d) More demand on one of the platforms (Yes/No)

20. Any other reasons you started working for multiple platforms?
21. When working for multiple platforms, are you worried about the following?

(a) I fear being penalized by platforms for multihoming (Yes/No)
(b) I understand one system much better than the other (Yes/No)
(c) I feel disloyal to the company working for both (Yes/No)
(d) I feel disloyal to my friends/community working for both (Yes/No)
(e) Working for both platforms is distracting/I can't focus on one (Yes/No)
(f) It is difficult to maintain ranking on one platform (Yes/No)

22. What would make your work EXCLUSIVELY for a platform and not multihome? (Select all that apply)

(a) Higher bonus on this platform
(b) Higher Income on this platform
(c) More orders/demand on this platform
(d) No penalty to multihoming
(e) All my friends/community shifting to this platform
(f) Others (please specify)
(g) None of these will make me change to working for only one platform

23. Anything else we should know about your decision to use multiple platforms?

B.3. Driving activities

Note: This set of questions are also asked for Grab and Go-Jek if respondents select Grab or Go-Jek in Question 1. We only show questions for Shopee in this section, which has one additional Shopee-specific question compared to Grab and Go-Jek.

For the next set of questions, think about your activity only for Shopee for the last 30 days

24. Which Shopee service did you take most orders from?
(a) Food (b) Other (c) No specialization
25. **[Shopee-specific question]** What has changed when Shopee appears?

(a) I drive less for Go-Jek
(b) I drive less for Grab
(c) I drive more for Go-Jek
(d) I drive more for Grab
(e) No changes

26. What type of area do you spend most of your online search time for Shopee?
    (a) Central areas (b) Outskirts
27. Out of the following, Which area do you spend most of your online/search time for Shopee in?
    (a) North Jakarta (b) South Jakarta (c) East Jakarta (d) West Jakarta (e) Central Jakarta (f) Other areas (Bodetabek)
28. What days a week do you usually drive for Shopee at least one trip? (Select all that apply)
    (a) Monday (b) Tuesday (c) Wednesday (d) Thursday (e) Friday (f) Saturday (g) Sunday
29. How many hours do you typically work for Shopee on these days?
    (a) Weekdays (0–24)
    (b) Weekends (0–24)
30. For the last two weeks: What has been your average daily salary from Shopee on weekdays? (in Rp)
31. For the last two weeks: What has been your average daily salary from Shopee on Saturdays and Sundays? (in Rp)
32. How many kilometers have you driven on average daily for Shopee when on bid [If more than 300, move the slide to maximum value]? (0–300 KM)
33. How satisfied are you with Shopee's:
    (a) Bonus Scheme (1–5)
    (b) Daily Income you make on the platform (1–5)
    (c) Matching system (1–5)
    (d) Responsiveness to driver complaints/problems (1–5)
34. When working for Shopee, approximately how many days do you hit your bonus?
    (a) All the time (b) Around half the time (c) Less than half the time

B.4. Sociodemographic information

35. What is your age?
    (a) Under 20 (b) 20–29 (c) 30–39 (d) 40–49 (e) Above 50
36. What is your gender?
    (a) Male (b) Female (c) Non-binary/third gender (d) Prefer not to answer
37. What is the highest degree you obtained?
    (a) SD (b) SMP (c) SMA (d) D3 (e) S1 or higher (f) None of the above
38. Is Grab/Go-Jek your main source of income?
    (a) Yes (b) No
39. How many people do your income support (not including yourself)? (0–10)
40. Approximately how much do you spend on food each week? (in Rp)
41. How much do you spend on rent each week? (in Rp)
42. What is your kecamatan (city district)?
43. What is your kelurahan (neighborhood)?

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