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# Information Design for Platform Drivers

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## Abstract

With the rise of app-based matching platforms, gig workers become important suppliers of labor to transportation and food delivery. An important dimension in the management of this labor supply are pricing decisions by platforms. This thesis makes a case for the importance of another dimension of platform design for platform drivers: Demand information given to drivers. Using a large-scale survey and platform-provided data, we give evidence for the relevance of demand information for drivers' labor supply decisions. We then start our investigation into how information should be designed, and derive policy recommendations for platforms and their regulators.

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# Chapter 1

# Introduction

> [Gig economy,] the collection of markets that match providers to consumers on a [job] basis in support of on-demand commerce. [. . . ] Prospective clients request services through an Internet-based technological platform or smartphone application that allows them to search for providers or to specify jobs. Providers (gig workers) engaged by the on-demand company provide the requested service and are compensated for the jobs.
> – Congressional Information Service, TOCITE

See the classical [27] for competition.

Questions of multi-homing (For Ridesharing [23], For quesitons of multi-homing [3], For benefits of multi-homing [5], for network migration, [9] for platform migration, [17] for a model shownig captive consumers) are orthogonal to our question.

Uber highlights flexibility of drivers [31].

## 1.1 Information Design for Platform Drivers

This thesis studies the relevance of demand information to platform drivers and how it should be designed.

[14] study the effect of ridesharing on urban mobility and find that ridesharing intensifies urban challenges.

Preference for flexibility is documented in several studies, also empirical of nature. [1] uses a choice experiment with virtual license plates for gig workers. Gig workers give up significant payments for working with . See also [21].

By platform drivers we mean all food or grocery delivery drivers and ridesourcing drivers. While formally offering distinct services, in many urban spaces, platforms offering ridesourcing, so-called Transportation Network Companies (TNCs), also offer delivery of food or groceries. Examples of TNCs—which all offer also delivery services—are Grab and Gojek in Southeast Asian countries, Didi Yuching in China and several South American countries, as well as Uber in a large part of the world.

The Congressional Information Service's definition of gig work highlights the opportunity of search for consumers. However, it does not mention search, or any form of information acquisition by gig workers.

In most of gig work, and in particular in driving for platforms, gig workers need to make important decisions which require information or expectation on the demand for rides or deliveries: When to work, where to work, and for how long to work. Not only do these decisions have an impact on driver earning, but also on TNC operations.

Information that could affect decisions of gig workers to supply or not supply their labor often takes the form of demand information. For example, information on an area or a time period of high demand for rides can affect drivers' earnings.

This information becomes particularly crucial as platform drivers usually do not set prices for their services.

While information provision to platform driver influences decision-making of drivers, information provision becomes also important for other parts of the gig economy. For example, knowledge of demand and expectations have been demonstrated in the market for freelance software development TOCITEwhen the market environment changed, or in investments into AirBnB housing TOCITE.

This thesis focuses on the design of information to drivers. It highlights that merely considering *pricing*, i.e. the setting of prices to consumers and gig workers, might be beneficially complemented by considering *information provision*, both for TNC operations, a market for third-party information providers and regulation.

After positioning platform drivers in the spheres of urban transportation and the gig economy in the rest of this chapter, and reviewing important dimensions of platform design which interact with information design and information provision through third parties in chapter 2, we make three contributions.

The first part of our study, chapter 3 investigates which other factors besides expected earnings affect driver labor supply decisions. In a large survey of platform drivers in Jakarta, Indonesia, we find significant inconsistencies with earnings maximization of drivers in terms of reported earnings, and find cultural, as well as informational aspects in drivers' labor supply decisions. We also find that drivers often do not reposition themselves, but follow the algorithm whenever possible.

We supplement our observations on the relevance of non-pricing TNC design questions in chapter 4 using earnings differences in platform-provided data. We provide an approximate value of demand knowledge using earnings differences under optimal *repositioning*, i.e. movement of idle drivers to other areas in the city. We make this estimate by inferring real earnings for platform driver trips undertaken for TNC DiDi Yuching in November 2016 in Chengdu, China and comparing the earnings differences to average earnings of delivery drivers on the platform. We find that optimal repositioning, which can be seen as a very strong form of knowledge of demand, can lead to significant (at least two-fold) increase in earnings if a small group of drivers is perfectly informed about demand.

Third, we take first steps into the design of information for platform drivers in **??**. In a benchmark model we formalize properties of the informational environment. We first show that never providing the same demand information to all drivers is welfare-maximizing. We show that in our model, an informational Braess' paradox arises, which is distinct from existing notions of an informational Braess' paradox.[1] We expose that platform drivers might ignore information presented to them by the platform as a result of limited commitment of a TNC which does not allow them to credibly commit to not maximize their revenue with a choice of information. We

[1] Manxi Wu studies this in road networks; Manish Raghavan studies it for several classification technologies TOCITE.

show that third-party information aggregators can remedy this inefficiency, as can a change in the payment structure of gig drivers, and that aggregators can do so even with information provided to all subscribed drivers, as long as these are a small proportion of all drivers.

The final chapter 6 collects policy recommendations both for TNC operators and regulators. We first show that information design is of different significance for TNC operators and regulators. While the former will need to rely on third-party aggregators to commit to disclosing information in a way that drivers will not ignore, and are in this endeavour aligned with drivers, the latter should think more carefully about equity in the proposed models: Information needs to be provided asymmetrically. While asymmetrically, it still needs to require that drivers are equally treated. We conclude with engineering challenges arising from our observations.

While we provide several facets of information design for platform drivers, we largely abstract both pricing (who pays what) and matching (which driver gets to serve which rider) decisions and competition concerns away. Real-world platforms solve joint optimization problems of pricing and information in competition with other platforms. While this means that all of our analysis needs to be seen as having a narrow view of the design possibilities of platforms, we highlight, on the contrary, that viewing platform design purely as a *pricing* question might fall short of optimal mobility platform design.

Our analysis can also only be seen as mid-term, as information design to Autonomous Vehicles will depend on whether all vehicles are centrally controlled and cooperative or not. Throughout this thesis, we maintain that platform drivers are human.

## 1.2 Background

Platform drivers take an increasing role in urban mobility (subsection 1.2.1), and have special characteristics compared to other forms of gig work (subsection 1.2.2). Some of these characteristics have led to more prominent regulatory interventions into platform driving (subsection 1.2.3). Regulators have for the biggest part not intervened into information provision to drivers, which puts drivers into a status quo of an information environment given by their TNC apps and third parties aggregating information (subsection 1.2.4).

### 1.2.1 Platform Drivers and Urban Mobility

As of 2021, services provided by platform drivers now make up $1/3$ of the global taxi market TOCITE. With the rise of the first transportation network companies about 15 years ago, the rapid changes leaves many of the design dimensions of this market open.

An important difference to other travel modes such as public transit is the need for dynamic rebalancing, i.e. ensuring a distribution of drivers such that in each part of the urban area expected ride demand can be met at each point in time. While dynamic rebalancing is also an important question in public transit operations, schedules can be designed with much less uncertainty.

Part of the uncertainty making dynamic rebalancing hard comes from the need to design incentives that ensure participation. Even with accurate demand models for riders, platform drivers usually have the opportunity to log off their platform or reject (some of) the rides requested by a customer. If they are not incentivized to continue working on the platform, they will not.

Incentive designs for a supply side of mobility have historically been less prominent in transportation research TOCITE. This opens an opportunity for the introduction of tools used in competitive supply of labor.

### 1.2.2 Platform Drivers as Gig Workers

Platform drivers are also gig workers *qua* the definition introducing this chapter. Riders search on the platform and are matched to a driver for their ride or delivery. Nevertheless, platform drivers are extreme in some of their characteristics.

First, platform driving is, compared to other parts of the gig economy very flexible.

This characteristic comes from the nature of gigs being short. Compared to other parts of the gig economy, e.g. lodging (e.g., on AirBnB, gigs usually at least one day), and services for care (e.g., care.com), technology (e.g., Andela), design (e.g., 99designs) and home services (e.g., Porch), typically require scheduling or completion within at least a day. This makes management of incentives compared to drivers

Second, the terms of the contract are fully determined by the platform. This is in contrast to other platforms such as in lodging, technology and design, where gig workers can set their own prices.

Third, reaching out to customers outside of the platform is much more challenging for platform drivers than for other gig workers. Compared to other gig work, giving a ride on the platform is short, and as both the complete contract and all payments are processed by the platform, it is hard for drivers to build gigs independently of the platform. This gives the platform additional bargaining power in negotiations with the driver.

Fourth, many of the drivers are full-time and work many hours a day. This both raises concerns over work safety, but also over wage bounds, some of which have been introduced as regulations.

### 1.2.3 Regulation of Platform Driver Work

Flexibility, limitations on contracting and communication, and the ubiquity non-wage controlled, full-time work led to policy interventions regarding minimum wages and the employment status of platform drivers.

The New York City Transport and Limousine Commission introduced an earnings standard which guaranteed a *proxy* minimum wage for ridesourcing drivers in New York City [25]. Drivers earn for rides an additional amount to increase the average as calibrated against historical demand data to the minimum wage level.

In 2020, California accepted via a referendum a special provision for ridesourcing drivers to be excluded from legal sufficient conditions for an employment relationship.

In contrast, the UK Supreme Court decided that ridesourcing drivers *are* employees of TNCs, with labor implications for drivers, with effects for payment and insurance of dirvers.

These regulations do not include provisions on the information that drivers get from TNCs, and other actors work in this sphere.

### 1.2.4 Platform Drivers' Payment and Information Environment

Most platforms drivers face an app on a smartphone, which offers them potential gigs, which they can accept or reject. At each point in time, drivers can select to log off the system, which drivers report to use strategically TOCITE. In the U.S. TOCITEand in our survey conducted in Jakarta (chapter 3), we find that a minority of drivers has several apps open at the same time. Hence, drivers are limited in their ability to observe demand on the other platforms.

This interacts also with payment design of platforms. Many platforms associate bonuses with the acceptance of rides, or punishments up to being blocked on the platform for not accepting ride requests. This makes being online in different platforms complicated for many drivers.

An important distinction will be three time periods, which we call, in accordance with nomenclature introduced by Uber TOCITE*phases 1, 2, and 3.*

Phase 1 corresponds to times where the driver is online but idle. In these times, the driver is not sent ride requests and does (except for bonus payments for repositioning) not earn money.

Phases 2 and 3 refer to the time between the acceptance of a ride request and the pickup of the passenger, and the ride, respectively. In these phases, riders are paid.

The goal of this thesis is to establish the relevance of providing drivers with demand information, and will only significantly affect driver behavior in phase 1. Drivers that are picking up or driving a rider have a clear task, and even a contract for their work. The main question we ask in our theoretical section will be when the platform can transmit any information that will not be ignored.

# Chapter 2

# Related Work

Information can add another dimension to driver behavior. In this section, we review studies that relate both in goal and in methodology to ours.

## 2.1 Platform Design

Stated that matching/allocation

In a mobility setting, the three tiers of information design, pricing and information are distinct but interesting of unified models of matching [16]. This paper studies how to thing integrated of systems. Information design cannot be represented in this view.

We view information design mostly for a monopolistic setting and view it for future work. Views about third-party integration are orthogonal to our question [37].

### 2.1.1 Matching

General matching is solved in the OR literature. TOCITE(dynamic stochastic matching with limited time)

An observation in the literature on matching is the Wild Goose Chase. A small number of drivers move far for.

[11] makes this point. [34] shows in a more general environment that this insight holds.

The dynamic rebalancing problem also shows up in bikes, [4].

### 2.1.2 Pricing

Some studies directly factor in that platforms might compete on idleness and price. This assumes that platforms internalize the prices that drivers get from their work [10]

Behavioral assumptions in Bayesian games are very peculiar [15, 28]. As an approximation, [28] assumes that at random time points drivers reconsider where to go given information on expected pay in an area.

[22] takes into account in pricing what happens to drivers that move around while moving to another place.

### 2.1.3 Information

In the focus group study [2], drivers report mislead repositioning guidance as a factor for improvement. We support this point in chapter 5.

Except for in routing games ([33], [30], [32]), informaiton design has not arrived in transportation very much. [33] studies a model of competing information providers, which are restricted to public informatoin to drivers. As they, we find inefficiencies arising from only interacting with one platform.

[29] shows using data from New York City that the highest welfare gains arise in less dense areas. In particular, these are areas where the informational component of platform design is particularly crucial.

[13] study as an early application strategic environments with many players and derive practical models. They find that in environments with stategic substitutabilities, asymmetric information provision can be desired.

[20] study a two-sided market in which groups are uncertain about the joining decision of the other side of the market.

While we do not study this, information and mechanism design come together. [24] proposes a model for incentivizing drivers to move to a new location with monetary incentives. We discuss below in chapter 5 how this system involves implicitly asymmetric information to drivers, and could be replaced by pure information design if commitment was possible.

#### Driver Behavior

There are also study that do not view information design as a platform question.

[**Chaudhari_Byers_Terzi_2018**] design an earnings-maximization strategy for drivers and show that strategic behavior about when and where to drive have significant impact on drivers' earnings.

In the literature on order dispatching, farsighted algorithms solve the dynamic rebalancing problem. [35]

### 2.1.4 Preference Elicitation

[36] study mobility sharing as a preference matching environment.

### 2.1.5 Asymmetry in Platform Design

Asymmetry to leverage network externalities are well-known in the network externality literature. [19] studies a model of a one-sided platform with network externalities, and devises how a platform would optimally price to agents. The optimal pricing involved.

## 2.2 Methodology

### 2.2.1 Survey Methods

### 2.2.2 Estimating Online Time of Drivers

### 2.2.3 Mechanism Design

Papers showing the impact of multi-homing use either stylized models such as those inspired by Hotelling lines [**bryan2019theory**, **bakos2020platform**], assume exogenous models of [**castillo2017surge**] or do not model multi-homing decisions [**liu2017impact**].

To understand platform pricing, many platforms

### 2.2.4 Scraping-Based Studies

Some platforms scrape data from platforms, such as studies on platform competition in New York TOCITE(rosaia) and a consumer surplus comparison of taxi and ridesourcing TOCITE(shapiro). Similarly, TOCITE(peaking under the hood) uses large-scale simulation of apps.

[12] deploy several copies of the Uber smartphone app to estimate pricing, in particular surge pricing, and mak observations on fairness of pricing.

### 2.2.5 Information from Platforms

The solution concept that can be created by targeted information design, Bayes correlated equilibrium, comes from [7].

### 2.2.6 Gathering Driver Data

Other papers assume that in moments where agents join a platform, they have exact knowledge of the surplus that is gained and the prices that both sides receive [**liu2019multihoming**].

[**Wang_Yang_2019**] offers a comprehensive review on the ride-hailing system including demand, supply and platform perspectives. Driver behavior is modeled differently in the ride-hailing literature. Regarding operations and optimizations for ride-hailing platforms, e.g., driver-customer matching, idle vehicle rebalancing and vehicle routing, drivers are assumed to follow the instructions of platforms ([**Bertsimas_Jaillet_Martin_20** **Alonso-Mora_2017**, **Braverman_Dai_Liu_Ying_2019**, **Wen_Zhao_Jaillet_2017**]).

Simple driver behavior models are proposed in the pricing literature of the ride-hailing system. [**Bai_So_Tang_Chen_Wang_2019**] propose a queuing model to optimize platforms' profit while considering price-sensitive customers and earning-sensitive drivers. Each driver has a reservation earning rate based on his outside option and the driver will provide services only if earning rate exceeds the reserved value. [**Taylor_2018**] evaluate the impact of uncertainty in passenger delay sensitivity and driver independence on platforms' optimal per-service price and wage. Each driver has an opportunity cost and the driver will participate in the platform when having non-negative expected utility.

[**Jiang_Kong_Zhang_2021**] show that regret aversion and ignorance of suggestion are the two major behavioral factors which influence drivers' re-positioning decisions.

## 2.3 Cheap Talk and Information Design

Our third contribution contributes to a line of work on cheap talk and information design.

### 2.3.1 Cheap Talk

The standard model of Crawford-Sobel TOCITE, in which one agent, which has a piece of information, communicates with another agent, who can take an action affecting both agents' utility, too strong mismatch of incentives leads to no communication. A classical model of cheap talk, communication is costless, and does neither binds sender nor receiver to take a particular action in the future TOCITE(Farrell). In our first model of information provision, we model the strategic interaction between the platform and drivers as a cheap talk game, and show that if the incentives of the platform and drivers diverge sufficiently, that, in equilibrium, no information is transmitted, in terms of the cheap talk literature, the platform *babbles*.

### 2.3.2 Bayesian Persuasion and Information Design

In contrast to cheap talk, Information Design models allow the sender to commit to rules for which information they reveal TOCITE(kamenica gentzkow, also annual reviews). This can have profound implications for the outcome compared to Cheap Talk. This will also be a feature in our model in chapter 5.

### 2.3.3 Information and Mechanism Co-Design

We build on a literature in information design [8]. [6]

While we consider a pure mechanism design problem, work on the co-design of mechanisms and information, such as TOCITE(mechanism design with aftermarkets). This paper considers the informational effect of allocations. In our platform driver setting this would model the informational effect of surge prices for rational drivers.

# Chapter 3

# Non-Monetary Shapers of Supply Decisions

> Since Uber's introduction in 2009, ridesharing platforms like Uber, Didi, Grab, and Lyft have radically transformed the taxi and limo industry. These services, which allow consumers to order a car to their location via a smartphone application, now control roughly 1/3 of the international taxi market. In other words, a ridesharing firm acts as a platform matching drivers to riders and setting the pricing terms between them. —TOCITE

This chapter analyzes results from a survey in Jakarta and shows significant departures from earnings maximization among platform drivers in Indonesia. We highlight context in free-text answers to gather evidence for reasons outside of earnings maximization.

## 3.1 Survey

We analyze data from a survey conducted in spring 2021 in Jakarta, Indonesia.

### 3.1.1 Sample

Participants were asked to complete an online survey hosted on Qualtrics and received 846 complete survey responses after being distributed and circulated to drivers through known social media (WhatsApp groups) used by drivers.

Figure 3-2a shows the age distribution of participants, where around 50% of drivers are within the age group of 30 to 39. Figure 3-2b reveals that over 97% of drivers who participated in the survey are male and around 97% are motorbike drivers.

There exist three major ride-hailing companies in Jakarta: Grab, GoJek and Shopee. While Grab and Gojek are incumbents in this market, Shoppee entered the market only in 2021. Figure 3-1 shows the percentage of drivers working for each of the platforms, double-counting multi-homers. Around 94% of drivers work for the incumbents Grab or GoJek. In our sample of drivers, only 12% of drivers questioned in the survey are multi-homers.

We are not aware of demographics of TNC drivers in Jakarta and hence unable to verify representativity of our sample.

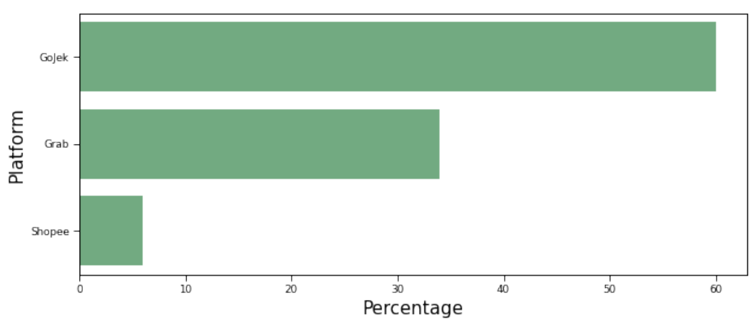
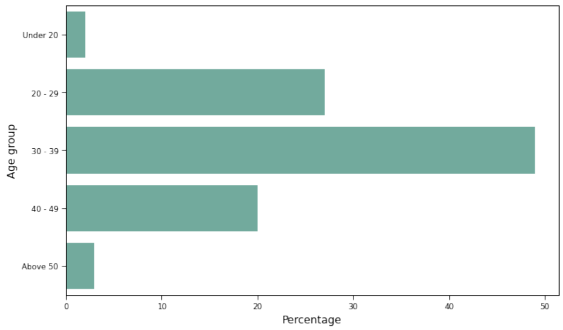



Figure 3-1: Platform distribution of drivers. (GoJek: 60%, Grab: 34%, Shopee: 6%)

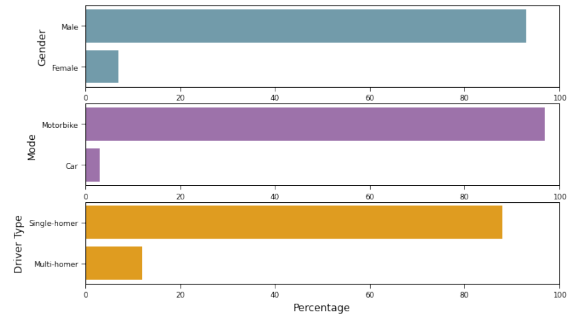
### 3.1.2 Questions

The survey consists of multiple questions blocks and is given in its entirety in Appendix A.

In a first block, participants were asked to check all TNCs they have been working for in the past 30 days. A survey respondent is defined as a *multi-homer* if they have




(a) Age distribution of drivers. (Below 20: 2%, 20 to 29: 27%, 30 to 39: 49%, 40 to 49: 20%, above 50: 3%)




(b) Gender, mode and driver type distributions of drivers. (Male: 97%, female: 3%; motorbike: 97%, car: 3%; single-homer: 88%, multi-homer: 12%)

Figure 3-2: Sociodemographic information and driving behaviors of survey participants.

been working for at least two platforms in the past 30 days. In this first block, basic information and driving behavior are asked as well, e.g., vehicle type used, previous occupation, behaviors while waiting for a next ride/order.

The second block depends on whether respondents were identified in the first block as multi-homers or not. Multi-homers are asked how they switch between different platforms, allocations of their working hours and reasons for multi-homing. For non-multi-homers, reasons for non-multi-homing and factors that would make them multi-home are asked.

In a third block, for each ride-hailing platform survey participants have worked for 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.

Table 3.1: Results of regression models predicting multi-homing behaviors of ride-hailing drivers in Jakarta based on sociodemographic information

| **Variable** | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **Intercept** | 0.3168*** | 0.052 | 6.040 | 0.000 | 0.214 | 0.420 |
| **Age (30 - 39)** | -0.0455* | 0.025 | -1.786 | 0.075 | -0.095 | 0.005 |
| **Age (above 50)** | -0.1189* | 0.069 | -1.721 | 0.086 | -0.255 | 0.017 |
| **Male** | -0.1213*** | 0.042 | -2.911 | 0.004 | -0.203 | -0.040 |
| **Degree (bachelor's or higher)** | 0.1258*** | 0.044 | 2.840 | 0.005 | 0.039 | 0.213 |
| **Degree (junior high school)** | 0.0327 | 0.035 | 0.939 | 0.348 | -0.036 | 0.101 |
| **Ride-hailing as main source of income** | -0.0733* | 0.038 | -1.925 | 0.055 | -0.148 | 0.001 |
| **Age (40 - 49) and ride-hailing as main source of income** | -0.0480 | 0.033 | -1.474 | 0.141 | -0.112 | 0.016 |
| **R-squared:** | 0.033 | **Adjusted R-squared:** | | | 0.025 | |

Table 3.2: **Results of regression models predicting multi-homing behaviors of ride-hailing drivers in Jakarta based on previous occupation**

| **Variable** | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **Intercept** | 0.1276*** | 0.012 | 10.735 | 0.000 | 0.104 | 0.151 |
| **Motorcycle taxi driver before** | -0.0796** | 0.031 | -2.574 | 0.010 | -0.140 | -0.019 |
| **R-squared:** | 0.008 | **Adjusted R-squared:** | | | 0.007 | |

## 3.2 Findings

To understand the multi-homing behavior and who works for multiple ride-hailing platforms, we first constructed a Lasso regression model with the regularization coefficient 0.001 based on drivers' socio-demographic information, which were shown in Table 3.1.We find that male drivers whose age is between 30 to 39 and above 50 are less likely to multi-home in Jakarta market. Also, drivers are less likely to multi-home if working for ride-hailing platforms is the main source of their income. On the other hand, we find that drivers with higher degrees are significantly more likely to multi-home. Next, we observe the correlation between previous work as a motorcycle taxi driver before on multi-homing behaviors. The OLS regression model shown in Table 3.2 suggests that drivers who has been motorcycle taxi drivers before are less likely to multi-home in Jakarta market.

Table 3.3: **Results of regression models predicting multi-homing behaviors of ride-hailing drivers in Jakarta based on whether being part-time ride-hailing drivers**

| **Variable** | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **Intercept** | 0.1097*** | 0.012 | 9.258 | 0.000 | 0.086 | 0.133 |
| **Being part-time ride-hailing drivers** | 0.0441 | 0.032 | 1.384 | 0.167 | -0.018 | 0.107 |
| **R-squared:** | 0.002 | **Adjusted R-squared:** | | 0.001 | | |

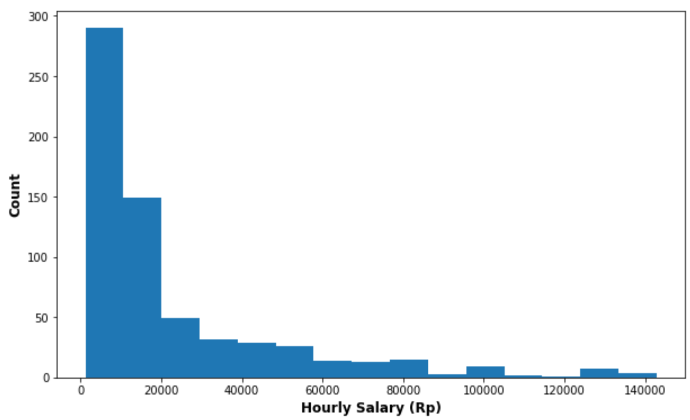



Figure 3-3: Hourly salary distribution of survey respondents (ride-hailing drivers in Jakarta)

Finally, we turn our attention to the results of our regression models exploring the impact of being a part-time ride-hailing driver on drivers' multihoming behaviors. From the model results shown in Table 3.3, we find that part-time ride-hailing drivers are more likely to multihome in our sample. However, it is a less significant predictor of multihoming behaviors compared to other variables above.

### 3.2.1 Earnings for Different Platforms

Then, we consider the Jakarta ride-hailing market and drivers' hourly salary and total working hours. Figure 3-3 displays the hourly salary distribution of all survey respondents in Jakarta, which fits into a negative binomial distribution. Most ride-hailing drivers earn less than 20,000 Rp (approximately 1.4 USD) per hour, which is significantly less than the average hourly salary 120,175 Rp (approximately 8.4 USD) in Jakarta [**Jakarta_hourly_salary**].

Table 3.4: **Results of regression models predicting hourly salary of ride-hailing drivers in Jakarta based on whether working for GoJek**

| Variable | coef | std err | z | P> \|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **Intercept** | 30710 | 2215.544 | 13.863 | 0.000 | 26400 | 35100 |
| **Only GoJek** | -11000 | 2547.137 | -4.319 | 0.000 | -16000 | -6009.224 |
| **R-squared:** | 0.038 | **Adjusted R-squared:** | | | 0.036 | |

Table 3.5: **Results of regression models predicting daily working hours of ride-hailing drivers in Jakarta based on whether working for GoJek**

| Variable | coef | std err | t | P> \|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **Intercept** | 10.6642*** | 0.162 | 65.928 | 0.000 | 10.347 | 10.982 |
| **Only GoJek** | 1.0335*** | 0.210 | 4.911 | 0.000 | 0.620 | 1.447 |
| **R-squared:** | 0.036 | **Adjusted R-squared:** | | | 0.034 | |

To understand whether drivers working for different ride-hailing platforms are payed differently, we constructed a regression model on the impact of working for GoJek on hourly salary, shown in Table 3.4. In this model, we only consider motorcycle drivers who work exclusively for one platform. The model results suggest that GoJek drivers earn significantly less than drivers from other platforms, 11,000 Rp (approximately 0.77 USD) less per hour.

Furthermore, we built another regression model to investigate the difference of total working hours between ride-hailing platforms. The model results in Table 3.5 show that GoJek drivers work significantly longer than drivers from other platforms, 1.0335 hours more per day. Both regression results imply that there existing a large switching cost between GoJek and other platforms (Grab and Shopee) in Jakarta ride-hailing market. GoJek motorcycle drivers work longer hours but earn less compared to other drivers.

### 3.2.2 Free-Text

In this section, we use a topic model (Latent Dirichlet Analysis) to discover potential non-monetary reasons for the choice of TNC that drivers work for. All of the analysis is use answers to question 16 (compare Appendix A) “Anything else we should know about why you decided not to use multiple platforms?”.

In a topic analysis, the word “focus” is highly descriptive of one of the clusters. Respondents indicate that “focus was needed for best results” and that they would not like to “confuse the apps”.

Others refer to the character of one of the platforms as being an Indonesian incumbent Gojek that competes with an (in our sample) better-paying incumbent from Singapore. Respondents make reference to “children of the nation” to underline their choices.

We use survey evidence showing that in an a significant share of non-multi homing drivers in an oligopolistic market for ridehailing in Jakarta. Our findings hint at substantial frictions to multi-homing, non-monetary incentives in the decision what TNC drivers choose to drive for, and when to drive.

#### 3.2.3 Discussion

As our evidence can only explain a small part of the variation in regression models, we propose other variables that could explain more of the variation in multi-homing and pay.

**Experience** Respondents mention *focus* prominently in reasons for multi-homing. To disambiguate whether this focus refers to learning of the platform or on permanent presence on the platform, joining date of the platform could be used as a proxy for experience.

**Risk Preferences** Another important explanation of variation in earnings could be given by the risk preferences of drivers. High variation in pay could stem from different behavior and different willingness to drive in times where getting a job from the platform are uncertain. Existing short surveys [**falk2016preference**] allow to estimate risk preferences.

# Chapter 4

# The Value of Information

After evidence from a survey, we move on with evidence derived from platform data.

we give evidence here on the value of information to drivers. This is aligned with claims by companies that offer information services to drivers TOCITE.

## 4.1 Description of Data

The DiDi KDD Challenge 2020, sponsored by DiDi Yuching, consisted of two challenge. An order dispatch challenge, and a driver repositioning challenge. We will work with data and submissions of the latter.

### 4.1.1 Annotated Order Data

We are given for November 2016 about 10 Million orders. An order consists of an origin-destination pair, a timestamp for beginning and end, an identifier for the driver that took the order, and a number of *reward units*. As the data is not publicly available anymore, we are unable to provide replication data for the following analysis.

A main challenge in our analysis is to recover the number of reward units corresponding to a RMB. Given our estimation below, we can transfer repositioning scores to monetary values, which gives us an estimate of

### 4.1.2 Reinforcement Learning Challenge Leaderboard

The KDD 2020 reinforcement learning challenge solves an optimal repositioning problem together with an optimal order dispatch problem. The problem is a partial observed semi-Markov Decision Process. In Reinforcement Learning language, which we review in **??**.

The system's observable state for the order dispatch algorithm consists of a list of orders to be dispatched at each point in time. This means a list of origin-destination pairs for orders, and for each driver timestamps of *estimated* order pickup and arrival times, as well as the distance for the driver. The reinforcement learning algorithm's actions are matchings of drivers to orders, the challenge does not consider carpooling. Orders need to be dispatched within two seconds, otherwise they are lost. (We specify the complete environment in **??**. As part of the state transitions, there is estimated data for cancellation probabilities when sending a driver to pick up orders from different locations.

The objective in the order dipatch algorithm is to maximize average driver income, which, as the system does not model drivers logging off strategically, is proportional to the total driver revenue in terms of orders completed.

The system's observable state for the driver repositioning challenge, which we are most interested in, consists of a set of drivers to be repositioned. There is a targeted group of drivers, which, after their first five minutes of being idle move according to historical transition probabilities between regions, can be repositioned. In addition to a timestamp, the only information given on drivers is a coarse position on a hexagonal grid of the urban area of Chengdu. The actions are, for each driver to be repositioned, a destination location. Agents are then repositioned at 3m/s in the spherical/great arc distance.

The objective in the driver repositioning problem is to maximize mean driver income rate for drivers. Denote $J_k^n(\pi)$ the online time for driver $k$ at day $n$ in hours.[1] Denote driver $k$'d income on day $n$ under policy $\pi$. For the set of all targeted drivers

[1]While the existing documentation do not specify the unit of this measure, our calculations below show that assuming online time is measured in hours leads to correct results.

$K$ and days $N$, the goal of the challenge was to maximize

$$\frac{1}{|K|} \sum_{k \in K} \frac{\sum_{n \in N} J_k^n(\pi)}{\sum_{n \in N} L_k^n(\pi)}.$$

We claim that the optimal repositioning score for drivers can give insight into the value of information for these drivers, as long as there are not too many of them.

If drivers have sufficient information about the demand throughout the city, they can reposition themselves to another location in expectation of getting higher earnings. As the maximization takes into account all online time, in particular the time moving to another area of the city, the earnings increase from a performant repositioning algorithm in this challenge can also be seen as a proxy for earnings of informed drivers.

In this argument, the small number of repositioned drivers is important. A challenge for drivers, but not for the platform, is that a knowledge on high demand in some area might lead to congestive effects—too many drivers enter high-demand areas.

But even with more drivers, private messages, which we discuss in chapter 5 help. Private messages is demand information (or, as we show, equivalently recommendations of to which area to move) only given to particular drivers, solving their

### 4.1.3 Earnings Table

We are using a publicly available table for earnings from 2021. In 2017, DiDi introduced two tiers of service for their drivers, Express and Premium. After personal conversations with experts, we use the table for express, reproduced in **??**.

The earnings table contains, dependent of the time of the day, a base price $b_t$, earnings per kilometer $l_t$ and minute driven $d_t$. At the time of the data, November 2016, additionally, a surge multiplier $s_t$. The total earnings $e_t$ for a ride of $L$ kilometers and duration $D$ are given by

$$e_t = s_t(b_t + l_t L + d_t D). \tag{4.1}$$

Table 4.1: Earnings for express drivers

## 4.2 Estimation

We assume in the following that reward units are a constant multiple of RMB. The underlying assumption is the following proposition.

**Proposition 4.1.** *Assume that reward units $r$ are a function $f$ of the earnings from an order in RMB. Assume that any policy generated for reward units is also optimal for policies in RMB. Then, the function $f$ is a constant multiplication, $f(x) = cx$ for some $c > 0$.*

### 4.2.1 Regression

We assume that a negligible fraction of rides uses a surge price and therefore estimate an equation simplifying (4.1),

$$e_t = b_t + l_t L + d_t D.$$

Our estimate of time is the times given in the order data. We use the Google Maps API to estimate distance in driving. The estimation results are presented in Table 4.2. We find highly significant and consistent estimates on the coefficients for distance and duration.

### 4.2.2 Checks

### 4.2.3 Model Fit

We observe that much of the variance can be explained by our model ($R^2 = 0.887$)

| | | | |
|---|---|---|---|
| **Dep. Variable:** | reward_units | **R-squared:** | 0.887 |
| **Model:** | OLS | **Adj. R-squared:** | 0.887 |
| **Method:** | Least Squares | **F-statistic:** | 1380. |
| **Date:** | Sun, 18 Jul 2021 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 14:45:52 | **Log-Likelihood:** | -2998.9 |
| **No. Observations:** | 2000 | **AIC:** | 6004. |
| **Df Residuals:** | 1997 | **BIC:** | 6021. |
| **Df Model:** | 2 | | |

| | **coef** | **std err** | **z** | **P> \|z\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **Intercept** | -0.1664 | 0.077 | -2.155 | 0.031 | -0.318 | -0.015 |
| **distance** | 0.3191 | 0.021 | 15.449 | 0.000 | 0.279 | 0.360 |
| **duration** | 0.0635 | 0.007 | 9.645 | 0.000 | 0.051 | 0.076 |

| | **coef** | **std err** | **z** | **P> \|z\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **Intercept** | -0.2569 | 0.262 | -0.981 | 0.326 | -0.770 | 0.256 |
| **rush_hour[T.True]** | 0.0095 | 0.320 | 0.030 | 0.976 | -0.618 | 0.637 |
| **distance** | 0.3318 | 0.047 | 7.113 | 0.000 | 0.240 | 0.423 |
| **rush_hour[T.True]:distance** | -0.0292 | 0.048 | -0.602 | 0.547 | -0.124 | 0.066 |
| **duration** | 0.0653 | 0.011 | 6.170 | 0.000 | 0.045 | 0.086 |
| **rush_hour[T.True]:duration** | 0.0028 | 0.014 | 0.200 | 0.841 | -0.024 | 0.030 |

Table 4.2: OLS Regression Results

## 4.3 Discussion

# Chapter 5

# Information Design

> The information design problem has a literal interpretation: there really is an information designer (or mediator, or sender) who can commit to provide extra information to players to serve her own interests. While the commitment assumption may be problematic in many settings, it provides a useful benchmark.–TOCITE

In this section, we study *pure* information design for platform drivers. We refer to it as *pure* as we study information provision while keeping the driver payoffs fixed. We show several limitations for the platform: Drivers, in equilibrium, ignore information if it cannot commit to not giving a particular driver some part of the information, it gives

## 5.1 Model

In our stylized model, two agents simultaneously decide whether to drive to a part of a city ("go") or to follow other business on or off the platform ("not go"). The platform observes a demand state $\theta \in \{0, 1\}$. We can view this as the outcome of an accurate demand prediction model. Before each of the drivers makes her decision on whether to drive, the system can send a message $m_1(\theta)$ to driver 1 and $m_2(\theta)$ to driver 2 on whether there is demand on the platform. Drivers get utility 1 if they get an order,

| Driver 1 \ Driver 2 | go | not go |
|---|---|---|
| go | $\frac{1}{2} - \varepsilon$, $\frac{1}{2} - \varepsilon$ | $1 - \varepsilon$, $\sigma$ |
| not go | $\sigma$, $1 - \varepsilon$ | $\sigma$, $\sigma$ |

(a) Demand, $\theta = 1$

| Driver 1 \ Driver 2 | go | not go |
|---|---|---|
| go | $-\varepsilon$, $-\varepsilon$ | $-\varepsilon$, $\sigma$ |
| not go | $\sigma$, $-\varepsilon$ | $\sigma$, $\sigma$ |

(b) No, $\theta = 0$

Figure 5-1: Payoff Matrix for the two-driver game.

and incur a cost of driving to the location of $\varepsilon$. This gives, depending on the demand state, the game tables in Figure 5-1

The platform gets utility of 1 if at least one of the drivers gets to the desired location, and 0 utility otherwise. The divergence of platform and driver utility stems from the payment structure for drivers, as we described in the introduction: Drivers only get paid for phase 2, when they are matched to a ride.

The platform can send messages to drivers. The platform can either send a message to drivers without committing to any particular form of information revelation (subsection 5.1.1) such as "I recommend you to go to this place, and I will not recommend this to others", or does not have the power to credibly commit to this (subsection 5.1.3).

We assume that the drivers best respond to the messages sent by the platform. In our first model, we assume that the platform can commit to a particular mapping from demand to messages, in the latter they cannot.

### 5.1.1 Information Design

We first study a setting where the platform can commit to an arbitrary mapping of demand $\theta$ to tuple of messages $(m_1(\theta), m_2(\theta))$. Before stating our theorem, we go into public or private information.

### 5.1.2 Public and Private Messages

Some information is shown to all drivers, while other is shown only to a few drivers. We call messages *public* if $m_1(\theta) = m_2(\theta)$ for $\theta = 0, 1$ and all other messages *private*. As is well-known in the information design literature TOCITE, the game that agents play is one of *strategic substitutes*, andp private information will increase the total utility for all players. In our case, this means, drivers. Our theorem adds that this is also the optimal choice of messages for the platform.

**Theorem 5.1.** *All maximizers of platform revenue are* $m_1(\theta) = \theta$*,*

### 5.1.3 Cheap Talk

In cheap talk, the platform discloses some information to a driver, which, given the update, updates their behavior. More concretely, there is an abstract set of *messages* $m \in \mathcal{M}$ that the platform can send. The players receive the message and play optimally. In particular, the timeline of the game is:

1. The demand $\theta$ at the area is realized.
2. The platform decides to send messages $(m_1, m_2)$ to the drivers.
3. The drivers decide to drive or not drive to the area.

We solve for perfect Bayesian (signalling) equilibria of this game.

**Theorem 5.2.** *In the cheap talk model, Perfect Bayesian equilibria have the following form:*

1. *If $\sigma < \frac{1}{2} - \varepsilon$ or $\sigma > 1 - \varepsilon$, then the platform is indifferent between any message, the drivers will visit their dominant choice.*
2. *If $\frac{1}{2} - \varepsilon \leq \sigma \leq 1 - \varepsilon$, the platform is indifferent between any message, and the drivers ignore the information.*

We show a proof to this statement in **??** If the general outside option is very low ($\sigma < \frac{1}{2} - \varepsilon$) or very high ($\sigma > 1 - \varepsilon$), drivers go to the area in hope to get a ride or stay away from it, respectively, even without demand information. The platform is indifferent between any demand information given that it won't influence the driver's decisions. This is an example where agents know that there is a high

In the other cases, the platform cannot transmit any information. The

In this environment, hence, if the not internalized cost from

## 5.2 Inefficiencies

After analysing the predictions, we identify two sources of inefficiencies: a potential lack of commitment (a comparison between our cheap talk and the commitment solution) and a potential lack of being able to provide asymmetric information.

### 5.2.1 Inefficiencies through lack of commitment

**Proposition 5.3.** *The cheap talk version of the game has lower welfare. This statement is uniform: Both platform and driver surplus are lower in the cheap talk game.*

The statement shows that neither side benefits from limited commitment of the platform. The drivers have to rely on less information, and cannot trust the platform. The equilibrium is "babbling".

### 5.2.2 Inefficiencies through public information

Comparing our second two theorems, we find the following loss from public information.

**Theorem 5.4.** *In the commitment regime, only allowing public information reduces platform and driver surplus. In the cheap talk regime, this restriction increases welfare*

This result might look somewhat surprising.

## 5.3 Remedies

Given the inefficiencies observed in the last section, some remedies for the market should be considered. We introduce two potential solutions to the platform's commitment problem, and one solution to the allocation problem.

### 5.3.1 Commitment via third parties

A main driver of the inefficiencies in our model was that there is a conflict of incentives between the platform and the drivers. In this environment, if drivers "pay" the platform, there is not much.

### 5.3.2 Commitment via reputation

A second opportunity for the platform to commit is via reputation. This assumes that the game of information provision studied in this section is repeated sufficiently often.

**Theorem 5.5** (TOCITE(Ellisson))**.** *In an infinitely repeated game with sufficiently patient agents, all individually rational payoffs can be achieved as a result of equilibrium play.*

This statement is allowed by agents playing a "punishment" equilibrium from the platform. It is unlikely in the setting of platform drivers that they can individually punish the platform, which, in return, does not incentivize the platform to give recommendations according to a commitment problem.

### 5.3.3 Approximate Efficiency of Public Information to Few Drivers

For our last statement, we will need a more general model. There are $n$ drivers, which learn a state $\theta \in \{0, 1, 2, \ldots, n\}$. Drivers get a utility $1-\varepsilon$ if matched to a ride and they get a utility of $-\varepsilon$ if not matched. We assume that $n$ is large, and a small fraction of drivers can get a public message.

**Proposition 5.6.** *Assume that drivers are*

## 5.4 Conclusion

This section presented a theoretical model

# Chapter 6

# Conclusion and Policy Implications

This thesis studied the relevance and optimal design of information provided to ridesourcing drivers. chapter 3 showed that besides earnings maximization, drivers also take into account cultural and infromational considerations in their labor supply decisions. chapter 4 showed that there are high potential earnings gains from additional information. We then went on to study commitment and privacy of messages as two challenges. In this last chapter, we consider three stakeholder groups, platforms, regulators and transportation engineers with policy recommendations and additional complications arising out of this work.

## 6.1 The Commitment Challenge for Platforms

We observed in chapter 5 that the limited commitment of the platform to providing different platform can lead to not information being transmitted and we proposed reputation

## 6.2 The Fairness Challenge for Transportation Regulators

## 6.3 Challenges for Transportation Engineers

The above two challenges give interesting challenges for transportation engineers.

### 6.3.1 Allowing for Commitment without Harming Businesses

### 6.3.2 Managing Fairness in Information Provision

# Appendix A

# Survey Questions for the Survey in Jakarta

## A.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) GoJek (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 bid?
   (a) Yes (b) No

7. Do you like this job more or less than working for Grab/GoJek/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 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)

## A.2 Multihoming Behavior

**For Non-Multi-Homers**

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 platform (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?

**For Multi-Homers**

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 platform (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 the 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 you 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?

## A.3 Driving Activities

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

**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 GoJek

    (b) I drive less for Grab

    (c) I drive more for GoJek

    (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 area (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 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

## A.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/GoJek your main source of income?

    (a) Yes (b) No

39. How many people does 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?

43. What is your kelurahan?

# Appendix B

# Complete Earnings Information for DiDi Platform Drivers

In this brief appendix, we reproduce payment information for platform drivers and describes more concretely the decision environment for the Reinforcement Learning agent in the KDD 2020 Callenge.

## B.1 Payment Information for Drivers

## B.2 Decision Environment for Reinforcement Learning Agents

Here, we describe the exact state and action spaces for Reinforcement Learning agents in the KDD 2020 challenge.

# Appendix C

# Omitted Proofs

# Appendix D

# Mathematical Background

## D.1 On Markov Decision Processes

Reinforcement learning is used in ridesharing [26].

[18] use the KDD data to estimate their value.

Here we introduce a notation on Markov Decision Processes

## D.2 On Statistical Experiments and Bayes-Correlated Equilibria

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