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Accept or Reject a Ride? This is the Problem*

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Abstract

Online ride-hailing platforms match drivers with passengers by forwarding ride requests to the nearest drivers. In this context, matching efficiency is jeopardized if drivers decline offers more often. Can the platform enhance efficiency and increase the drivers’ ride acceptance rates, and if so, by how much? What factors influence the drivers’ decisions to accept or reject offers? Are drivers more likely to turn down an offer because they know that by rejecting it, they can quickly receive another offer, or do they reject offers because they can easily find an outside option of a street-hailing passenger? To answer these questions, we use a novel dataset provided by Tapsi, a ride-hailing platform located in a Middle East country, Iran, and present a structural discrete dynamic programming model to evaluate how drivers decide whether to accept or reject a ride. Using this model, we quantitatively measure the effect of different policies to increase the driver’s acceptance rate. In our model, drivers compare the value of each offer with the value of outside options and the value of waiting for better offers before making a decision. We use the Simulated Method of Moments (SMM) estimation technique to match the dynamic model with our unique data from Tapsi and estimate the model’s parameters. We find that the low driver acceptance rate is mainly due to the availability of a variety of outside options. Therefore, even hiding information from or imposing fines on drivers who reject rides cannot greatly motivate them to accept more offers and does not affect drivers’ welfare by a large amount. The results show that by hiding ride information, the average acceptance rate increases by about 1.81 percentage points; while the increase is 4.5 percentage points if there were no outside options. Moreover, the results indicate that the imposition of a 10-minute delay penalty increases the acceptance rate by only about 0.07 percentage points. Finally, we find that other conditions being equal, price increases can boost the acceptance rate of offers, by large.

Keywords: Labor Supply Elasticity, Matching, Online Ride-Hailing, Information Disclosure, Two-Sided Market. JEL: R41, J22, J49, C63, C15, C55

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1 Introduction

Several ride-hailing platforms are operating worldwide with the common goal of facilitating the matching between drivers and riders. Matching efficiency increases as drivers accept offers at higher rates. Therefore, a critical question is what affects this acceptance rate and how much different policies such as changing commission fees, hiding some of the ride’s information from the drivers, or even penalizing the drivers who reject offers could motivate drivers to accept more offers, and what are the impacts of such policies on the platform’s revenue and the drivers’ welfare. In this paper, we shed light on the drivers’ decision-making process and measure the impact of policies that could potentially affect this process by using a novel dataset provided by Tapsi, a ride-hailing platform operating in Iran. We present a discrete dynamic programming model based on search and match theory to model a driver’s behaviour in accepting and rejecting offers and incorporate the Simulated Method of Moments (SMM) estimation technique to estimate the model’s parameters. We test the model using the data and run counterfactuals to assess the impact of policies that could potentially affect drivers’ acceptance rates.

Launched in 2017 in Tehran, the capital of Iran, Tapsi is a popular ride-hailing platform currently operating in more than 15 major Iranian cities. For the first time, we have employed a novel and extensive dataset provided by Tapsi to answer one of the most critical questions ride-hailing platforms face: how to increase matching efficiency. To the best of our knowledge, this is the first study using the data of a ride-hailing platform operating in the Middle East/Iran. We have access to six months of the data including all the ride offers sent to Tapsi’s drivers from January to June 2018 in Tehran. Our data includes an offer’s information such as the ride’s price, distance, origin, destination, and time of sending the offer, as well as the IDs of the passenger requesting the ride and the driver receiving the same, plus the driver’s decision. As we will explain in details below, Tapsi works differently from many other ride-hailing platforms such as Uber as it reveals much more information to the drivers regarding the offers and gives the drivers more freedom in making their decisions. Therefore, Tapsi’s dataset has several advantages and allows for assessing the impact of different counterfactuals that could change the drivers’ behaviours.

While some ride-hailing platforms such as Uber limit how much information is provided to the drivers regarding the ride characteristics at the time of sending the offers, some platforms such as Tapsi disclose all ride characteristics including price and destination to their drivers. Moreover, in contrast to Uber’s approach which imposes some form of penalty for drivers who frequently reject offers, in Tapsi, the drivers are free to reject a ride without any penalties. Although giving drivers more freedom might be attractive to them, it jeopardizes Tapsi’s objective of matching more drivers with riders instantly. A review of data reveals that Tapsi drivers have a relatively low acceptance rate, which is problematic as a lower acceptance rate is translated into higher waiting times for riders, who might eventually give up and use other ride services. Therefore, it is crucial to understand what factors influence the drivers’ decisions to accept an offer, and if taking a similar approach to other platforms could enhance the acceptance rates.

In this paper, we develop a dynamic programming framework that captures drivers’ behaviours in a platform that provides them with full information about a ride, including the price and destination, and gives drivers full freedom to accept or reject the ride. Our dynamic programming model works as follows: For a given driver, every combination of time, location, price, length of ride, and destination indicate one state. In each state, the driver compares the present value of accepting an offer in hand with the present value of rejecting the offer. The present value of accepting the offer depends on the ride’s characteristics,

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4 The data set is quite large, but we cannot report its exact size due to data confidentiality.
such as the price and the destination’s distance, as well as the quality and quantity of the offers a driver can possibly receive at the destination. On the other hand, the rejection of a ride enables a driver to receive an offer at the same location or quit the program and use outside options. An example of outside options is finding a passenger waiting for a street-hailing vehicle that’s not officially a taxi, but which commonly plies the streets of Iran. This enables Tapsi drivers to switch to a traditional mode for finding a passenger at any given time. Drivers are assumed to be rational agents who are aware of the distribution of offers and who compute the value of rejecting or accepting the offer and make a decision that maximises their gains.

We use Contraction Mapping Theorem to solve the dynamic programming problem.

The main parameters of the model are outside options available to a driver, depending on the time and location of receiving an offer, as well as the type of driver, variance of (random) outside options, and the cost of driving for each unit of time. These parameters are estimated using the SMM approach. In particular, we use 64 moments, including the weighted average acceptance rate of offers for any type of driver (4 types) and from any origin to any destination (4 modes), on weekdays, Thursdays, and Fridays, between 4:00 a.m. and 11:59 p.m. (48 moments) and the weighted average of acceptance rate by any type of drivers, from any origin to any destination, between 12:00 a.m. and 3:59 a.m. (16 moments). We estimate 11 parameters using these moments.

The results of the estimation show that drivers who have a Tehran number plate (and are able to work at Tapsi’s biggest competitor, Snapp) have around 4,300 Tomans more outside options compared to drivers with a non-Tehran number plate, in each working period. A working period corresponds to consecutive intervals where a driver works constantly, without taking a rest. Also, drivers who work full-time have outside options worth around 21,000 Tomans less compared to part-time drivers. Consistent with our intuition, on Thursdays and Fridays (weekends in Iran), and at midnights, outside options are lower. In addition, the estimated variance between outside options available to drivers is quite large (around 28,000 Tomans), which shows there is a large heterogeneity among drivers. Note that these numbers are reasonable as the daily minimum wage was around 34,000 Tomans on average during the period of our study. Also, the cost of driving for each unit of time (2 minutes) is estimated to be 69 Tomans, which is consistent with the cost of fuel at the time of our analysis. Moreover, the probabilities of continuing to work after rejecting a ride and after completing a ride are estimated to be 83.64% and 18.54% respectively. On average, the value of receiving a ride offer in a working period is estimated to be about 34,000 Tomans. According to the results, drivers with access to relatively large outside options tend to reject offers more often.

Given the model and the estimated parameters, we evaluate an alternative policy of hiding ride information, i.e., price and destination. The results show that since Tapsi drivers have the opportunity to use various outside options, uncertainty cannot significantly increase acceptance rates. For instance, hiding all the information from drivers increases acceptance rates by only 1.8 percentage points, while the average value of receiving an offer, which is equal to the welfare the driver attains from receiving that offer, declines by 3% when information is hidden. For similar reasons, imposing a penalty in the form of putting a driver in a time-out after rejecting a ride or reducing the likelihood of receiving an offer in the next interval cannot have a major impact on the drivers’ acceptance rates, as it would only increase acceptance rate by less than 1 percentage point. In the former type of penalty, the average value of receiving an offer would be reduced by 0.05%, and in the latter, by 1.12%. However, when setting part of the outside options to zero, hiding full information increases the average acceptance rate by 4.5 percentage points compared to the mode of providing full information. Therefore, we conclude that one reason Tapsi drivers are reluctant to accept offers even in the mode of concealing information and imposing penalties is that they have access to several outside options.
The rest of the paper is organized as follows. The next subsection interfaces this paper with the existing literature and highlights the differences. Section 2 introduces data and presents some stylized facts. In sections 3 and 4 the respective model and estimation approach are discussed. The results of the estimation are presented in section 5, and, finally, the implication of the model in the form of evaluating counterfactual policies is discussed in section 6.

Related Literature. This paper contributes to the literature on ride-hailing markets and investigates matching frictions caused by drivers’ decisions. In general, the literature on ride-hailing markets is extensive and scrutinizes various aspects of these markets. As an example of a two-sided market, ride-hailing platforms aim to match passengers and drivers instantly by using matching and dispatching algorithms. They also set the price of the ride, which affects both passengers and drivers. Not surprisingly, a vast part of the literature is dedicated to problems such as pricing (Bai et al., 2019; Hu and Zhou, 2019), dynamic pricing (Cachon et al., 2017; Castillo et al., 2017; Castillo, 2020; Riquelme et al., 2015), and matching and dispatching algorithms (Vazifeh et al., 2018; Özkan and Ward, 2020; Xu et al., 2018).

Ride-hailing platforms are the matching place for passengers (demand side) and drivers (supply side). Part of the literature focuses on the demand side of the market and studies issues such as demand elasticity and consumer surplus (Cohen et al., 2016; Moradi et al., 2020) or characterizing and forecasting short-term demand (Saadi et al., 2017; Ke et al., 2017; Buchholz et al., 2020). In contrast, another part of the literature pertains to the supply side of the market. Our paper relates to the latter group, as we study the discretion of drivers in accepting or rejecting offers.

Drivers in ride-hailing platforms are free to provide rides whenever they want. Chen et al. (2019) show that Uber drivers benefit from this real-time flexibility and earn more than twice the surplus they would in less-flexible arrangements. Wang and Yang (2019) point out that drivers who work in a ride-hailing platform face two decisions: whether to work (service supply at the extensive margin), and if so, when and for how many hours (service supply at the intensive margin). Studies such as Angrist et al. (2021) and Abbassiyan et al. (2019) focus on drivers’ labour supply in the form of working hours. In contrast to these papers, our paper evaluates drivers’ decisions concerning the acceptance or rejection of offers, which constitute another type of decision drivers face in a ride-hailing platform.

One paper that specifically considers accept/reject decision-making is Ponnachiyur Maruthasalam et al. (2018), which analyses a driver’s profit-maximizing strategy, defined as “best evaluation criteria to either accept or refuse a ride request”, using a derivative-free optimization method. The authors find that refusal based on proximity, i.e., “accepting the request only if the pick-up location is within a certain distance from the current location of the driver”, is the best strategy for drivers under most of the studied scenarios. Furthermore, in an empirical investigation, Xu et al. (2018) apply a logistic regression model to study factors affecting drivers’ decisions on accepting or declining a request. They conclude that economic incentives offered to drivers (in the form of subsidy), the characteristics of ride-hailing requests (geographical distance, number of repeated submissions), and the spatio-temporal supply and demand intensities are the main factors influencing a driver’s decision. In contrast to our work, in these papers, the price of the ride is not included in the information given to drivers. In addition, the dynamic nature of a driver’s decision-making process is not taken into account.

In evaluating the supply side of the ride-hailing market, some research focuses on the supply elasticity of drivers, i.e., the effect of hourly wages on drivers’ decisions to participate in the platform, and how many hours to work. In fact, labour supply elasticity of drivers has been under debate long before the emergence of ride-hailing platforms. In 1997, Camerer et al. (1997) used data on wages and hours of New
York City cab drivers and showed that wage elasticity is negative for these drivers. They concluded that the drivers had a daily income target and quit working when they reached that target. Later, Farber (2005, 2015) showed that drivers do not exhibit income-targeting behaviour and have a positive wage elasticity. Using the data from Uber, studies by Sheldon (2016) and Chen and Sheldon (2016) find no evidence of income-targeting behaviour and negative supply elasticity as well. Again, the literature in this area focuses on the effect of wages on drivers’ decisions concerning hours of work and does not consider the effect of wages on the acceptance rate of drivers.

Sourcing the data of Tapsi, Esterabi et al. (2019) focus on estimating the elasticity of drivers’ acceptance rate with respect to price using a regression discontinuity model. This study is similar to our paper, as it focuses on drivers’ decisions to accept offers. However, our work is different from this research as we take into account drivers’ dynamic decision-making process, and therefore we can assess counterfactual policies such as hiding information.

In examining the drivers’ decisions, we use a dynamic model inspired by the model introduced by McCall (1970). In his pioneering work, McCall (1970) built a dynamic model to capture the decisions of job searchers in accepting or rejecting job offers, in which searchers compare the value of accepting the job with the expected value of rejecting it and continuing the search later and decide whether to accept the offer. The problem of drivers deciding whether to accept a ride offer in a ride-hailing platform is somewhat similar to that of job searchers in the labour market, and we use the notion introduced by McCall (1970) to build our model. Search models are also applicable in other markets such as labour markets (Pissarides, 2000) and money markets (Bech and Monnet, 2016).

The refusal of offers sent to drivers results in friction in the process of matching drivers and passengers. Matching frictions in taxi markets have been the subject of numerous research. To study the search and matching frictions between passengers and drivers in conventional taxi markets, Yang et al. (2010) propose a Cobb-Douglas matching function that specifies the number of matches between passengers and drivers at any given time as an increasing function of the number of waiting passengers and vacant taxis. Following their approach, studies such as Zha et al. (2016) and Wang et al. (2016) use Cobb-Douglas matching functions to model matching in ride-hailing platforms. Moreover, Buchholz (2022) proposes a dynamic model of spatial search and matching between traditional taxicabs and passengers and shows that the common taxi regulations lead to substantial inefficiencies as a result of search frictions. This paper is especially related to our discussion as it focuses on drivers’ decisions, yet in the form of where to look for passengers, not whether to accept offers.

In the present paper, by introducing a model for driver’s behaviour, we evaluate the effect of hiding information from drivers. A relevant paper in this field is Romanyuk (2017), which studies information design in matching platforms, and concludes that full information disclosure is inefficient due to the possibility of excessive rejections by sellers. In the case of Uber, specifically, Romanyuk (2017) argues that when drivers have detailed information about ride requests and are given decision-making rights to accept offers, they will have the ability to “cream-skim”; i.e., after rejecting a passenger, a driver remains available on the platform and receives a fraction of subsequent ride offers that could otherwise be sent to the rest of the drivers. This has an adverse impact on the other drivers because they face fewer valuable offers and gain lower profits. Romanyuk (2017) also shows that instead of Uber’s current policy of fully concealing the destination of passengers, a partial disclosure policy could be more efficient.

In another similar study, Chu et al. (2018) show that giving drivers information about the ride origin and destination, along with letting them choose whether to accept or decline an offer, results in “strategic idling”, which means that drivers decline offers to compete with each other in choosing more profitable
rides. As a result, equilibrium profits may decline. To align drivers’ incentives, the writers propose a matching policy that reduces strategic idling behaviour. Note that although studies such as Romanyuk (2017) and Chu et al. (2018) focus on relatively similar questions posed by our study, our work differs in two main aspects: First, in our model, the information provided to drivers includes the price of the ride, whereas in these studies the information given to the drivers only includes the ride’s destination. Second, we evaluate information-concealing policies using data from a ride-hailing platform, whereas these papers only focus on theoretical aspects.

2 Data
2.1 Overview of Tapsi Ride-Hailing Platform

Tapsi is a ride-hailing platform based in Iran that matches passengers and drivers using an online application. According to Tapsi's CEO, around 300,000 ride requests were recorded at Tapsi daily in the period covered by our data analysis. Also, as mentioned by Iranian officials, around 15,000 drivers worked at Tapsi during a period close to our analysis. Tapsi offers three services that include Telephone Tapsi, in which passengers can request a ride by making a phone call, and Line Tapsi, in which passengers can share a ride with other passengers going to a similar destination. Our paper only focuses on the Classic Tapsi service, wherein passengers register their ride through a mobile application, without sharing their ride with others. Around 95% of the requests registered in Tapsi belonged to Classic Tapsi at the time of our analysis.

When passengers specify their location and the destination of their ride through their mobile applications, they see the price of their trip set by Tapsi based on dynamic pricing algorithms. After observing the price, passengers can request the ride. The ride request is sent to drivers in the order of their proximity to the passenger within a specified radius. The driver observes the passenger's location, destination, and price of the trip. Both the driver and the passenger view the same ride price. Tapsi's commission is fixed at 15% of the price for all the rides. After receiving a ride order, drivers have 15 seconds to accept the offer. As a result, every ride offer sent to a driver is either accepted or rejected, such that ignoring an offer within the given deadline implies rejection. There is no penalty for rejecting an offer. Hence, each ride request can end up either being fulfilled successfully, failing to find a driver, or being cancelled by the driver or the passenger before the ride is finished.

While Tapsi operated in more than 12 major Iranian cities during the time of our analysis, we have only considered ride offers in Tehran, the capital of Iran, in this paper. Tehran is the largest Tapsi market and after about two years of activity, it could be considered a substantial market in the period analysed here, while it was expanding in other cities.

2.2 Data Cleaning Process

We use the data of ride offers registered through the Classic Tapsi service in Tehran from January to June 2018. The dataset includes information on all requested rides and offers sent to drivers in that period. For each ride, we have the ID of the passenger requesting the ride, date and time of the ride registration (in milliseconds), price, latitude and longitude of origin and destination, and the estimated length of the ride, the distance between each driver receiving the request and the passenger, and the status of the ride (fulfilled,

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5 Due to data confidentiality, statistics directly sourced from the data provided to us cannot be mentioned here.
no driver found, cancelled). We also have the ID of drivers that receive the ride request, the type of their vehicle’s number plate (registered in Tehran or not), and their decision (to accept or reject).

For the data cleaning process, we identify successive ride requests with the same characteristics registered by the same passenger in less than 5 minutes and consider them as a single request, with the status of the ride equal to the status of the last recorded request. If a passenger requests a trip and does not find a driver, they might make a fresh request after a few minutes. Such duplication should not be considered distinct because they are inherently the same and without eliminating them, some of the features of the rides will be subject to overestimation. For instance, the number of requests is artificially increased when there are not many idle drivers and passengers are forced to repeat their requests. Therefore, in analysing requests, such successive ride requests are counted as only one.

We also drop the outliers from our raw data, including the top 1% and the bottom 1% of the rides with respect to their price, rides that have an estimated length of more than an hour (including less than 1% of the rides) and the 1% shortest trips, which removes rides in the bottom 1% of driver-passenger distance (less than 5 seconds) as well.

### 2.3 Summary Statistics

In this section, we provide the summary statistics of our data. Given all ride information, drivers that receive a ride offer can cherry-pick rides, that is, they can reject offers based on the given information and wait for offers that are more appealing to them. The profitability of the offer or other factors such as a driver's tendency for going to a particular destination, near their home for example, determine whether the driver finds the offer appealing. Figures 1 to 7 shed light on this aspect of drivers' behaviours.

First, Figure 1 shows the mean of the relative number of requests in each hour of the day, for weekdays (Saturday to Wednesday in Iran) and weekends (Thursday and Friday in Iran). A ride request refers to a request registered by a passenger. The number of requests is normalized to the mean number of rides in each hour of each day available in the dataset to maintain data confidentiality.\(^6\) The patterns of requests found here resemble the weekly patterns of demand in Uber presented by Castillo (2020). A ride request can be sent to different drivers in the form of ride offers. The acceptance rate is defined as the number of offers that are accepted by the drivers, relative to the total number of offers sent to drivers. Figure 2 presents the acceptance rate in each hour of the day for weekdays and weekends, where the acceptance rate is normalized to the percentage of accepted offers in the full dataset. Figure 3 shows the relative rate of ride requests that end up with no drivers matched with them. Again, we present the rate of no-driver-found requests normalized to its mean to protect data confidentiality.

Based on Figures 1 and 2, it is clear that on weekends, when the number of ride requests falls relatively, the acceptance rate increases. The same happens at midnight hours. In contrast, in peak hours when the number of ride requests increases, the acceptance rate drops. On the other hand, a comparison of Figure 2 with Figure 3 shows that when the acceptance rate is high, the percentage of requests with no drivers found drops and vice versa. This shows the importance of drivers having a high acceptance rate for the platform, as passengers may give up or use other ride-hailing apps when no drivers are found for their requests. As is seen in Figure 4, waiting times, defined as the time interval between when a request is

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\(^6\) Maintaining confidentiality of the data is based on the Non-Disclosure Agreement (NDA) contracted with Tapsi. All other statistics provided in this section will be normalized for the same reason.
submitted and when it is accepted by some driver, are also higher when the acceptance rate is lower, as expected. We run a t-test to examine the hypothesis that acceptance rate has a negative correlation with the number of rides and with the rate of rides that end up without being matched with any drivers. We use data on the number of rides, rate of rides with no drivers found, and acceptance rate in each hour of each day of the week (168 observations). Panel A in Table A.1 in the Online Appendix shows that the expected correlations exist and are significant.

The negative correlation between the number of ride requests and acceptance rate is not only observed in the time dimension, but also across different regions. In Figures 5a and 5b, Tehran is divided into 256 regions with equal areas based on geographical coordinates, and the intensity of the number of ride requests and acceptance rate is shown in each region. It is clear that overall, in regions of Tehran where the number of requests is intense, the acceptance rate is lower; whereas in regions where not so many requests are recorded relatively, the acceptance rate is generally higher. This negative correlation is also examined using a t-test. Panel B in Table A.1 indicates a significant negative correlation between the acceptance rate and the number of rides, and the number of rides with no drivers found, across the 256 regions of Tehran. The negative correlation between requests’ intensity and acceptance rate seen across time and location dimensions in Tapsi resembles the patterns found by Xu et al. (2018) which show that the driver response rates decline as spatio-temporal demand intensity increases in one of the well-known ride-hailing platforms operating in China.

From this evidence, we can hypothesize that drivers tend to reject more offers if they expect that they can receive a possibly more desirable offer in a short time when the number of requests is high enough. Therefore, they have a tendency to reject offers and cherry-pick the desired ones. On the contrary, at night or on weekends, or in places with less intensity of requests, the number of requests falls. The drivers know they have to wait longer to receive another offer and have less chance of receiving their desired offers in such situation; therefore, they will accept more offers. This correlation can be explained in another way as well. More intense requests also indicate a busy time or a more crowded place. In such hours or places, a lot of people are looking for a taxi; therefore, it is possible for a Tapsi driver to find passengers through other methods, such as the traditional method of street-hailing. In Iran, traditional street-hailing is possible for any vehicle, and drivers can easily pick up passengers who are waiting for a taxi along the street. On weekends or at night, there is less chance to pick up a passenger in this way, and therefore drivers have fewer outside options available, making them accept more offers.

The correlation of outside options’ availability with the acceptance rate can be examined from another viewpoint as well. Tapsi’s largest competitor, Snapp, which is another ride-hailing platform operating in Iran, did not allow drivers who owned a vehicle with a non-Tehran number plate to work in Tehran at the time of our analysis, whereas there was no such restriction in Tapsi. As a result, drivers working in Tapsi and having a Tehran number plate could receive offers from Snapp at the same time. On the other hand, those having a non-Tehran number plate vehicle were deprived of this option. Figure 6 confirms that the latter group has a higher acceptance rate, perhaps because they had fewer options outside of Tapsi. The t-static of the t-test on the difference between the mean acceptance rate of the two groups at every hour of the day of the week is equal to 16.74. With 168 observations in each group, the difference is significant at the 1% significance level, and the t-test indicates that non-Tehran number plate drivers have a higher acceptance rate.

Given the ride information, many factors can affect a driver’s choice of accepting an offer. Intuitively, the higher the price, the more likely the driver is to accept offers, provided that distance remains constant. Figure 7 brings evidence for this intuition. In this figure, the price of the ride is divided by the
estimated length of the ride, defined as the sum of the passenger-driver distance plus the estimated distance between origin and destination (both in minutes). According to Figure 7, the higher the price per minute of the trip, the higher the acceptance rate. It is noteworthy to mention that the figures in this section indicate correlation and not causality. In the next section, a model is proposed that captures the driver’s decision-making process based on the profitability of rides, the probability of receiving more profitable offers, and available outside options.

3 Model

In this section, we introduce a dynamic programming model to analyse a driver’s behaviour in rejecting or accepting offers. In this model, when a driver receives a ride offer, they must decide whether to accept the offer or reject it by comparing the expected value obtained from each of the two choices. The expected value of accepting the offer is proportional to the offer’s properties such as price and length of the trip. Also, upon arrival at the destination, the driver receives the next ride offers there; therefore, the value of accepting a ride offer also depends on the expected value of the offers that the driver will receive at the destination. In addition, when a driver arrives at the destination, they may decide to go offline and enjoy the outside options available at that destination instead of receiving the next offers. For instance, every driver has the option to pick up passengers in the traditional street-hailing way or can receive offers from other ride-hailing platforms if they have signed up on those platforms as well. Also, the driver might have other options like going to their workplace or their home which brings some value for them. Therefore, after completing a ride, if the driver wants to continue working, they should compare the value of the destination’s outside options with the expected value of staying online on the application and receiving new offers. Also, after completing a ride, the driver may want to take a rest and stop working, in which case the expected value they will receive is zero.

Rejecting an offer, on the other hand, allows the driver to receive other offers at the same origin in the next period. In addition, if the driver does not want to receive other offers in the next period, they can exit the application and use the available outside options. Therefore, if willing to work, the driver compares the expected value of subsequent offers with the value of outside options and obtains the maximum value of the two. In addition, the driver may want to rest for the next period and stop working. Therefore, the value of rejecting a ride offer is equal to the maximum expected value of possible offers in the next period and the value of the outside options available in the next period (again, we consider the expected value of resting to be zero).

In sum, the value of a ride offer for the driver is equal to the profitability that the driver gains from making the optimal choice against the offer. Drivers are rational, have full information, and engage in a dynamic decision-making process to decide whether to accept or reject an offer they have been proposed. Figure 8 summarizes the drivers’ decision-making process underlying our model.

3.1 Setup

Given the above intuition, a driver’s decision-making process can be modelled as follows. Consider a driver \( n \), located at origin \( i \) at time \( t \), holding an offer with price \( p \) to destination \( j \). The trip takes \( x \) periods to complete. The value of holding the offer for the driver is
\[ V_{n,i,t}(p,x,j) = \max\{ (p(1 - \text{com}) - cx) + \beta_d \max\{ u_{n,j,t+x}, OP_{n,i,t+x}\}, \beta_r \max\{ u_{n,i,t+1}, OP_{n,i,t+1}\} \} \]

in which,

\[ u_{n,k,t} = \mathbb{E}_{p',x',j'}[V_{n,k,t}(p',x',j')]\mathbb{P}_{k,t} + \beta_r \max\{ u_{n,k,t+1}, OP_{n,k,t+1}\}(1 - \mathbb{P}_{k,t}) \]

and

\[ \mathbb{E}_{p',x',j'}[V_{n,k,t}(p',x',j')] = \sum_{p',x',j'} f_{k,t}(p',x',j') V_{n,k,t}(p',x',j') \]

In equation Error! Reference source not found., the value of a ride offer is equal to the maximum value of rejecting or accepting the offer. If the driver accepts the offer, a value of \( p(1 - \text{com}) - cx \) is obtained by the driver, in which \( c \) is a constant that converts the negative value of the trip length into a price unit. For example, \( c \) could indicate fuel cost and depreciation per unit of length, or any disutilities received from working \( x \) amount of time. The parameter \( \text{com} \) determines the commission multiplier of Tapsi which is deducted from the price. The driver arrives at the destination at time \( t + x \) and continues to work with probability \( \beta_d \). Here, work is defined as either staying online in Tapsi or going for outside options. In other words, \( 1 - \beta_d \) is the probability that the driver quits their working shift to take a rest, and therefore receives a value normalized to 0. Note that after accepting a ride, the driver should complete it and cannot decide to leave work before the ride is finished. Furthermore, we have assumed that the probability of wanting to work at the destination is not a function of the length of the trip, to simplify the model. If the driver continues to work, they achieve the maximum expected value of being online in Tapsi \( u_{n,i,t+x} \) and receiving a ride offer or leaving the application and gaining outside options. The value \( u_{n,j,t+x} \) is calculated using Error! Reference source not found.. If the driver rejects the offer, they will continue to work in the next period, i.e., at \( t + 1 \), with probability \( \beta_r \), in which case they achieve the maximum value of exiting the application and going for outside options or staying online in the application and receiving \( u_{n,i,t+1} \). \( u_{n,i,t+1} \) specifies the expected value of being online in the Tapsi application and waiting to receive an offer at location \( i \) and time \( t + 1 \), and is calculated using Error! Reference source not found.. In equation Error! Reference source not found., \( u_{n,k,t} \) is the expected value of being online in the Tapsi application and waiting to receive an offer at location \( k \) and time \( t \). The driver will receive an offer with probability \( \mathbb{P}_{k,t} \). Conditional on receiving an offer, the driver’s gain will be equal to the expected value of all offers that they may receive. This expected value is calculated according to equation Error! Reference source not found., by using the probability distribution function of the requested rides, \( f_{k,t}(p',x',j') \). On the other hand, if a driver does not receive an offer, they will have to wait one period to receive another offer. The driver will continue to work in the next period, with probability \( \beta_r \), and thus, obtains a value equal to the maximum value of being online in Tapsi at the same location \( u_{n,k,t+1} \) and the value of exiting the application and going for outside options \( OP_{n,k,t+1} \) in the next period. The driver may also want to stop working and rest, in which case the value gained will be zero by our normalization assumption. It is clear that according to the timing of the model, the driver first decides to stay online or log out and then receives a ride offer. In other words, the driver only compares the expected value of the next offers with the outside options. Also, note that we have assumed that if the driver does not receive an offer in the current period, they will continue to work in the next period with probability \( \beta_r \), which is the same as the probability of wanting to work in the next period after rejecting a ride.
The reason for the difference between the probability of continuing to work after completing a ride with the probability of wanting to work after rejecting an offer or failing to receive an offer is that in the former, the driver has completed a ride and reached the destination, therefore factors such as fatigue may reduce the likelihood of continuing to work. As a result, we expect $\beta_r > \beta_u$. We should also emphasize that $\beta_u$ and $\beta_r$ capture drivers’ willingness to supply work and are both assumed to be exogenous to the model, as the focus of our model is on the driver’s behaviour in the intensive margin. In other words, we want to measure how drivers make decisions about accepting rides conditional on deciding to continue working.

Finally, our model shows the value of an offer in the price unit, and all values of the outside options are in this unit as well. The driver’s decision-making process is dynamic, and it terminates when the driver decides to quit the application or decides to stop working. In this way, the expected value of receiving a ride offer, $V$, the value of staying online in Tapsi, $u$, and the value of outside options, $OP$, are calculated for a period of working constantly. In fact, one gains value only from working, and when they are comparing the value of being online on Tapsi or going for outside options, the two values are the values the driver can obtain by working constantly before taking a rest.

**Outside Options.** In the presented model, the outside options available to the driver are the options that the driver can have access to if they exit the Tapsi application. The outside option $OP$ has two components: one is a deterministic part and is a function of the driver’s type, $y_n$, represented as $op(y_n)$, and the other is a random part denoted as $\epsilon_n$. So, for driver $n$,

$$OP_{n,k,t}(y_n) = op_{n,k,t}(y_n) + \epsilon_n$$

(4)

where $\epsilon_n \sim \mathcal{N}(0,\sigma)$ by assumption. Also, we assume that the deterministic part of the value of the outside options, i.e., $op_{n,k,t}(y_n)$, is the sum of the fixed effects of the factors affecting the outside options:

$$op_{n,k,t}(y_n) = op_k + op_t + op_{typeOfWork} + op_{plate}$$

(5)

where $op_k$ shows the value of the outside options at location $k$, $op_t$ indicates the value of the outside options at the time unit $t$, and $op_{typeOfWork}$ and $op_{plate}$ refer to outside options related to the type of work the driver does (part-time or full-time) and the type of the driver’s vehicle’s number plate (Tehran or non-Tehran) respectively. We explain each of these factors below.

Outside options’ availability may vary over time and location. For instance, on weekends, the possibility of finding a passenger by street-hailing decreases. Conversely, this type of finding passengers is more possible during working hours and working days. Similarly, outside the city centre, the outside options available to drivers are different from those in the city centre. These differences are considered in our model as outside options are specified to be a function of location and time.

Outside options also depend on drivers’ characteristics. To model these differences, drivers are categorized in two ways. First, drivers are categorized into full-time and part-time drivers. For full-time drivers, the number of rides they complete in a day is greater than the 75th percentile of the number of rides completed by one driver per day in the dataset. The distinction between full-time and part-time drivers is because full-time drivers are likely to have no source of income other than Tapsi, and therefore, accept more rides, all other conditions being the same. In addition, as explained in the previous sections, drivers with non-Tehran number plates were not able to work in Tapsi’s largest competitor, Snapp, at the time of our analysis. Therefore, they have fewer outside options available. So, we divide drivers in terms of their
vehicles’ number plates as well. The combination of full/part-time and Tehran/non-Tehran number plate categories makes four types of drivers, denoted by $y_n$.

At the same time, many other factors affect the driver’s decision and are not visible to us. For example, drivers may be looking for offers with destinations close to their regular workplace. These preferences come as a shock to the model, and we can only talk about their distribution.

The next step is to define the estimation strategy for estimating these outside option parameters along with other parameters of the model. The estimation strategy is explained in section 4.

### 3.2 A Discussion of Modelling Assumptions

The model described in this section relies on certain assumptions. First, it is assumed that when a driver decides to leave the application, as long as they want to work, they acquire a value equal to the value of the outside options available to them and do not go online again. This is generally not true because the driver can log into the app again after a while. However, this assumption does not call into question the general implication of our model because our model examines the driver’s decision in a period of constantly being online.

Another assumption is that upon arriving at the destination, the driver receives subsequent offers at the same location. Also, after rejecting an offer, the driver stays at the same location. This assumption is intended for simplicity and does not affect the overall implication of the model. In estimating the model, we will divide Tehran into two large areas, and therefore limited movements of the drivers will not change their location.

In addition, it is assumed that drivers are fully aware of the distribution of the offers they would receive, as they can calculate the expected value of future offers in their decision-making. In fact, drivers may not be fully aware of this distribution function, but they often have a general estimation of the probability of receiving possible offers.

Another assumption is that the probability of receiving an offer is the same for all drivers, because $\mathbb{P}$ and $f$ are not functions of driver’s type. This assumption is valid because Tapsi only considers the driver-passenger distance in sending ride offers and does not consider the type of driver.

In addition, parameter $c$ is assumed to be the same for all drivers. This assumption is also intended for simplicity and can be discarded without changing the overall insight of the model. Similarly, Tapsi’s commission is the same for all drivers and is applied to the price of the trip. This assumption is consistent with Tapsi’s mechanism as the commission rate is a fixed percentage of the price during our analysis.

Finally, it is assumed that the random part of the outside options has a normal distribution. This assumption is very general and allows the values of outside options for drivers to be positive or negative and very small or very large.

### 4 Solution Algorithm

In equations `Error! Reference source not found.` and `Error! Reference source not found.`, $V$ and $u$ are Bellman functions. For $V$, the state variables are $n, i, t, p, x, j$, and for $u$, the state variables are $n, i, t$. We consider the state variables to be discrete and apply discrete dynamic programming methods to solve for $V$ and $u$ numerically for any set of state variables.

We discretize the state variables related to location, time, price, and length in the following way. The finite set of locations is obtained by dividing Tehran into central and non-central areas. To divide
Tehran in this way, we group the areas that are subject to the Air Pollution Control Program as the centre of Tehran. These areas cover the central parts of the city and are usually more crowded than other parts of Tehran, as most of the businesses and administrative offices are in these parts. The rest of the areas are grouped as the non-central category. Figure A.1 in the Online Appendix shows this division.

The state variable $t$ denotes time intervals in terms of every two minutes of an hour of a day of the week. That is, every period in our model is equal to a two-minute interval of a day of the week. Therefore, we have:

$$t \in \mathbb{T} = \{0, ..., 7 \times 24 \times 30 - 1\}$$

To discretize price, we divide rides into four categories based on their price: rides with cheap prices (less than 10,000 Tomans), rides with average prices (between 10,000 to 15,000 Tomans), rides with high prices (between 15,000 to 20,000 Tomans) and rides with very high prices (more than 20,000 Tomans). For each category, we consider the weighted average of the price of the rides requested in that category as its representative. We cannot mention these averages here due to data confidentiality.

The length of trips (summation of passenger-driver and origin-destination distance) is also categorized into short and long rides. To do this, we compute the median length of the trips. All rides with lengths less than the median length of the trips are categorized as short rides and the rest are long rides. Exact numbers cannot be mentioned here due to data confidentiality.

**Solving the dynamic programming model.** For solving equations Error! Reference source not found. and Error! Reference source not found., we use the contraction mapping theorem (C.M.T). Given any initial value for vectors $V$ and $u$, we consider the contraction mapping function $\mathbb{T}$ as follows:

$$TV_{n,i,t}(p,x,j) = \max\{(p(1 - \text{com}) - cx) + \beta_u(\max\{u_{n,j,t+x}, OP_{n,i,t+x}\}), \beta_r \max\{u_{n,i,t+1}, OP_{n,i,t+1}\}\}$$

(6)

Similarly,

$$Tu_{n,k,t} = \mathbb{E}_{p',x',j'}[V_{n,k,t}(p',x',j')] \mathbb{P}_{k,t} + [\beta_r \max\{u_{n,k,t+1}, OP_{n,k,t+1}\}](1 - \mathbb{P}_{k,t})$$

(7)

According to the C.M.T, Bellman functions have a fixed point, and starting from any initial vector, by applying the contraction mapping function for enough iterations, they converge to the same fixed point. This point is the unique solution of the Bellman equation. In this way, functions $V$ and $u$ are solved numerically for all the possible states.

To show how functions converge, consider a hypothetical case with two drivers, one location and two different time intervals, four values for price, and a fixed value for ride length. We set the value of the non-random outside options to zero and assign a random value for each driver as the value of the outside option. In Figure A.2 provided in the Online Appendix, the diagram on the left shows how function $V$ converges as a function of price, all other states being constant. The figure on the right depicts function $u$ for the same driver at the same location and time. Starting with an initial vector, both functions eventually converge to certain values. Function $V$ is increasing in price. The cut-off point in this function indicates the threshold price before which all offers are rejected, and after which, all offers are accepted.

By having these functions in hand, we can obtain the drivers’ policy function. This function determines whether a driver accepts a given ride offer or not, in any set of state variables, given parameters. The $\Omega$ policy function for driver $n$ is defined as follows:
\[
\Omega_{i,t}(n,p,x,j) = \begin{cases} 
1 & (p(1 - \text{com}) - cx) + \beta_d (\max\{u_{n,i,t+x}, OP_{n,i,t+x}\}) \\
0 & \geq \beta_r \max\{u_{n,i,t+1}, OP_{n,i,t+1}\} \\
\text{Otherwise} 
\end{cases}
\]

This function is used later to obtain the moments needed to estimate the parameters.

**Identification and Estimation of Parameters.** Knowing how to solve the dynamic programming model, we should specify the strategy for estimating parameters. Some of the parameters of the model can be obtained directly from the data. First, the parameter \text{com} indicates the percentage of Tapsi commission with respect to the ride price. This commission is equal to 15% of the price in the period under review and therefore \text{com} is set to 0.15.

Moreover, the probability distribution function of ride requests at location \(i\) at time \(t\) \((f_{i,t}(p,x,j))\) can be obtained from the data by finding the ratio of the number of rides requested from location \(i\) at time \(t\) to destination \(j\), with price \(p\) and length \(x\) divided by the number of all rides requested from location \(i\) at time \(t\). Specifically, this function indicates the probability that a driver at a specific location \(i\) and time \(t\) will receive a ride of price \(p\), with length \(x\) to destination \(j\).

In addition, the probability that a driver will receive an offer while being online on the application at location \(i\) at time \(t\), \(P_{k,t}\), can be estimated from data as well. The probability of receiving an offer depends on three different factors: the number of requests \((r)\), the number of online drivers \((o)\), and the average number of drivers that receive the offer \((m)\). The values of these variables can be calculated from the data, and the probability that a driver will receive an offer at time \(t\) at origin \(i\) is equal to:

\[
P_{k,t} = 1 - \left(1 - \frac{m}{o}\right)^r
\]

The other model parameters are \(\beta_r\), \(\beta_d\), \(c\), \(\sigma\) and parameters related to outside options. As mentioned in the previous section, the deterministic part of outside options is specified as the sum of fixed effects related to location, time, type of driver in terms of being part-time or full-time, and the number plate of the vehicle, noted as \(op_k\), \(op_t\), \(op_{typeOfWork}\) and \(op_{plate}\), respectively. Areas of Tehran are divided into two groups, central and non-central, and therefore \(op_k\) takes two forms: \(op_{k=central}\) and \(op_{k=non-central}\). Similarly, we have the two modes for \(op_{typeOfWork}\): \(op_{typeOfWork=full-time}\) and \(op_{typeOfWork=part-time}\). In addition, \(op_{plate}\) takes two forms: \(op_{plate=Tehran}\) and \(op_{plate=non-Tehran}\).

Regarding the \(op_t\) parameter, it is important to note that since time is defined here as intervals equal to every two minutes of a day of the week, and since estimating the time parameter for every two minutes is not logical, the time intervals should be grouped to form different categories of the time fixed effect. To do this, we consider the time from 4 a.m. to 11:59 p.m. as one group, and from 12 a.m. to 3:59 a.m. as another group, denoted by \(op_t(day)\) and \(op_t(night)\) parameters, respectively. The rationale for this classification is that at midnight, outside options are reduced and therefore considered separate from other hours of the day.

Outside options related to time not only depend on the time of the day but also vary with the days of the week. Therefore, we divide the days of the week into three categories, weekdays, Thursdays, and Fridays (Thursdays and Fridays are weekends in Iran), and denote the outside options related to the days of

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\footnote{Proof of this formula is available in the Appendix.}
the week by parameter \( op_t(dow) \). This parameter takes three modes, \( op_t(Weekdays) \), \( op_t(Thursday) \) and \( op_t(Friday) \). We assume that at midnight, there is not much difference between available outside options on weekdays or weekends, whereas available outside options vary over the days of the week during the daytime. Therefore, for the time intervals from 4 a.m. to 11:59 p.m., we add \( op_t(dow) \) to \( op_t(day) \).

As only the sum of the outside options matters for the driver, we need to normalize the value of certain modes of outside options to zero to identify the parameters. Equation (5) does not have an intercept; therefore, we do not normalize any of the location fixed effects. For the rest of the parameters, \( op_{type=part-time} \), \( op_{plate=non-Tehran} \), \( op_t(night) \) and \( op_t(Weekdays) \) are normalized to zero.

Overall, we have 11 parameters to estimate. To do so, we use the Simulated Method of Moments (SMM) approach, using 64 moments related to the driver’s acceptance rate. The same 64 moments are used in estimating all parameters. Specifically, the moments used in estimating parameters are the weighted average of the acceptance rate of offers for each type of driver (4 types), from any origin to any destination (4 modes), on weekdays, Thursdays, and Fridays, between 4 a.m. to 11:59 p.m. (48 moments) and the weighted average of the acceptance rate by type of driver, from any origin to any destination, between 12 a.m. and 3:59 a.m. (16 moments). In this way, we have 64 moments that we must obtain from the model and match with the corresponding moments derived from the data. To obtain the moments from the model, the random part of the model, \( \epsilon_n \), must be simulated. We simulate 1000 drivers for each type of driver, having 4000 simulated drivers overall. The drivers’ decisions to reject or accept offers in each state are derived from the \( \Omega \) policy function. The expected acceptance rate will be equal to the portion of offers accepted in each category corresponding to the moments defined.

Thus, if we represent the state variables with \( s \) and the model parameters with \( \Theta \), and define vector \( m \) as follows
\[
\hat{m}(s, \Theta) = \text{AcceptanceRate}_{data} - \mathbb{E}[\text{AcceptanceRate}(s, \Theta)]
\]
we must obtain parameters such that
\[
\hat{\Theta}_{SMM}(s) = \arg \min_{\Theta} \hat{m}'(s, \Theta) \|W \hat{m}(s, \Theta)
\]
(10)

where \( W \) is equal to the identity matrix \( I \). Our objective function to minimize will then be the sum of the squares of differences between the moments obtained from the data and the model. To minimize this function, we use the method introduced by Nelder and Mead (1995).

In calculating the moments from the model, it is necessary to pay attention to the fact that in the policy function \( \Omega \), we obtain drivers’ decisions for all possible combinations of price, length, and destination. Some of these combinations are more common and some are less common in the data. For example, the combination of a long ride with a low price is very rare in the data. Therefore, in calculating the acceptance rate using the policy function \( \Omega \), we give weights to each set of price, length, and destination. The weights are proportional to the frequency of each combination of price, length, and destination in each origin and time category, relative to all ride requests registered in that origin and time category, in the dataset. In this way, the weighted average of the acceptance rate is calculated for obtaining moments from the model, and we can compare this to the moments obtained from the data.

In the next section, the results of the estimation and interpretation of the parameters are given.
5 Results

Using the procedure explained in the previous section, we estimate the parameters. The results of the estimation are shown in Table 1. In addition, since functions are also estimated in the dynamic programming model, the average values for the estimated functions $U$ and $V$ are presented in Table 1 as well. In the rest of this section, we discuss the results.

The parameter $c$ is a constant that converts the negative value of the trip length into the price unit. The value of $c$ indicates that every two minutes (time unit in our model) of a ride decreases profits by 69 Tomans. In the period under our analysis, the price of petrol was 1000 Tomans per litre, fixed by the government. If we consider the average fuel consumption by vehicles in Tehran as 7 litres per 100 kilometres, and if we assume the average speed of driving in Tehran is equal to 25 kilometres per hour, the cost of petrol for every two minutes will be approximately 58 Tomans. Since expenses attributed to a ride include costs such as depreciation and the price of petrol, the estimated value of $c$ seems to be consistent with our intuition.

Also, the results show that holding other parameters constant, drivers with Tehran number plates have outside options worth 4320 Tomans more than the value of outside options available to drivers without Tehran number plates, in each working period. A working period corresponds to consecutive time intervals in which the driver works constantly, without taking a rest. This difference shows that on average, having more options such as working in a competitor company increases the value of outside options by 4320 Tomans. (The value of outside options for non-Tehran number plate drivers is normalized to zero). On the other hand, the value of outside options available to full-time drivers is 21259 Tomans less than the value of outside options available to part-time drivers in each working period. (For part-time drivers, the value of outside options is normalized to zero).

In addition, on Thursdays, in each working period, the value of outside options is 2976 Tomans less than on working days. This difference is larger when comparing Fridays with working days and is equal to 4692 Tomans (The value of outside options on working days is normalized to zero). Furthermore, in the central areas of Tehran, the value of outside options is 37786 Tomans per working period. This value is not very different outside the central areas of Tehran and is equal to 36923 Tomans in those areas. From 4 a.m. to 11:59 p.m., outside options are worth 8110 Tomans more than outside options at midnight in a period of working constantly (The value of outside options at night is set to zero).

The standard deviation of the simulated outside options is 27915 Tomans, which indicates that, as expected, there is a lot of heterogeneity among the drivers. The $\beta_a$ parameter indicates how much the driver is willing to continue working if a ride is completed. The estimated value of this parameter indicates that a driver continues working after completing a ride with an 18.54% probability. The $\beta_r$ parameter indicates how much a driver is willing to continue working if they reject an offer. Based on our estimation, after rejecting an offer, there is an 83.64% chance that the driver continues working in the subsequent time interval.

Figure 9 shows the relationship between the moments obtained from the model and those of the data. As can be seen from the figure, the model moments are well consistent with the data. As explained in the previous section, these moments include 64 moments, including the weighted average acceptance rate for each type of driver, from any origin to any destination, during the working days, Thursdays and Fridays, and midnight hours of all days of the week. Acceptance rates are normalized due to the confidentiality of the data.
For better comparison, Figure A.3 in the Online Appendix shows all the moments used in the estimation obtained from the data and the model. The time intervals shown in this figure correspond to the time intervals considered for the moments (4 a.m. to 11:59 p.m. for weekdays, Thursdays, and Fridays, and 12 p.m. to 3:59 a.m. for all days of the week). Again, numbers are normalized due to the confidentiality of the data. According to Figure A.3, the relative acceptance rate has the same trend in all the origins and destinations. This rate is higher for each group at midnight than at 4 a.m. to 11:59 p.m. on weekdays, Thursdays, and Fridays. Also, the acceptance rate of each group on Fridays and Thursdays is higher than on working days. On the other hand, at any origin-destination and at any time, full-time drivers with non-Tehran number plates have the highest acceptance rate and part-time drivers with Tehran number plates have the lowest acceptance rate. These patterns are almost similarly repeated among the acceptance rates derived from the data. The price and length of the ride also affect acceptance rates. Figure A.4 in the Online Appendix shows the average acceptance rate from each origin to each destination over the price of the rides for long and short trips. As the figure depicts, in any price range, shorter trips have higher acceptance rates. The difference diminishes as the price increases. This pattern is repeated in all origin-destination modes.

To validate the accuracy of the estimates, we consider the moments of the data and the model that are not used in the estimation. To do this, we obtain the weighted average acceptance rate for each type of driver, from each origin to each destination, at each price and length of ride categories, on working days, Thursdays, and Fridays. In this way, we obtain 384 moments to compare the results of the model with the data. Figure A.5 in the Online Appendix shows the scatter plot of data and model moments. As it is clear in the figure, in most cases the moments of the model and the data are close to each other.

Two important factors in accepting or rejecting offers are the value of being online in Tapsi at a location and time (equation 2) and the value of outside options at that location and time. Table A.2 in the Online Appendix presents the average value of outside options and the average value of being online in Tapsi at each time interval and location, by type of driver. As shown in the table, the average value of outside options from 4 a.m. to 11:59 p.m. on weekdays is higher than the average value of outside options at the same hours on Thursdays and Fridays. Also, at midnight, the outside options available to drivers are reduced. Among the groups of drivers, part-time drivers with Tehran number plates have the largest outside options and full-time drivers with non-Tehran number plates have the smallest outside options. These results are consistent with our intuition because drivers with Tehran number plates can register with Tapsi’s competitor ride-hailing company. Also, it seems that full-time drivers probably work full-time because they have fewer outside options available. The existing pattern for the value of outside options also applies to the value of being online in the Tapsi application. As we know, the value of being online in Tapsi at a given location and time, according to equation Error! Reference source not found., is related to the value of outside options in the next period. The probability of receiving a ride offer as well as the probability of receiving a higher value offer are also influential in determining this value.

Table A.2 also shows the average value of receiving an offer at a specific time and place (equation 1). The observed pattern for the value of receiving an offer is similar to the observed patterns for the value of outside options and the value of being online in Tapsi. The average value of a ride offer for different prices and lengths of rides is depicted in Figure A.6 in the Online Appendix. The average value is larger for higher-priced trips. Also, longer trips, other factors being the same, reduce the value of the offer.

Through the proposed model, it is possible to calculate what is the threshold price for accepting an offer for each driver, for any time, location, destination, and ride length. Based on the model, a price threshold is a price where the driver rejects offers with a lower price than the threshold price and accepts offers of a higher price, with other ride properties staying the same. This is because if a driver accepts an
offer with a certain price, they will also accept higher-priced offers, ceteris paribus. For example, in Figure A.7 provided in the Online Appendix, the price threshold is obtained for a given simulated driver receiving offers at a given location at the first two minutes of each hour of the day. At midnight, other conditions being fixed, the driver accepts 15-minute offers that are in the price range of 10 to 15 thousand Tomans or more. This price threshold increases during these hours for 30-minute trips and is equal to the range of 15 to 20 thousand Tomans. During the day, the price threshold for 15-minute trips raises to the category of ride prices of more than 20 thousand Tomans and the driver does not accept 30-minute trips.

6 Counterfactual Analysis

In this section, we examine the effect of some counterfactual policies using the values obtained for the parameters in the previous section. First, we examine the effect of hiding all or part of the information from drivers. Moreover, we evaluate the impact of imposing fines in the form of delay in receiving the next offer or reducing the likelihood of receiving the next offer. We evaluate the impact of each of the scenarios on driver acceptance rates, the average value of a ride offer, and the average value of being online in Tapsi. We also examine the impact of reducing the Tapsi commission rate.

6.1 Hiding Information

As mentioned in the introduction, some ride-hailing companies around the world encourage drivers to accept offers by hiding information such as price and destination from drivers at the time of sending them a ride offer. Using our parameter estimations, we can modify the model to evaluate the result of hiding such information on drivers working in Tapsi. First, we hide all the ride information, i.e., price, length, and destination of the ride from the driver. Thus, the value of an offer received by driver $n$ at time of $t$ and origin of $i$ is:

$$V_{n,i,t} = \max\{\mathbb{E}_{p',x',j'}[(p'(1 - com) - cx')] + \beta_a(\max[u_{n,j',t+x',OP_{n,j',t+x'}}]), \beta_r \max[u_{n,i,t+1}, OP_{n,i,t+1}]\}$$  \hspace{1cm}  \text{(11)}$$

in which,

$$u_{n,k,t} = V_{n,k,t}(1 - \mathbb{P}_{k,t})$$  \hspace{1cm}  \text{(12)}$$

and,

$$\mathbb{E}_{p',x',j'}[((p'(1 - com) - cx')] + \beta_a(\max[u_{n,j',t+x',OP_{n,j',t+x'}}])$$

$$\equiv \Sigma_{p',x',j'}f_i(t, p', x', j')[(p' - cx')] + \beta_a(\max[u_{n,j',t+x',OP_{n,j',t+x'}}])$$  \hspace{1cm}  \text{(13)}$$

In equation Error! Reference source not found., $f$ is obtained the same way as in Error! Reference source not found.. To compare the change in the acceptance rate in this case with the benchmark mode where all the information is provided to the drivers, we obtain the weighted average of the acceptance rate from any origin at any time, for a driver in both modes. In this way, we can compare the average acceptance rate over all origins, times, and drivers. The results show that by hiding the information, the average acceptance rate increases by about 1.81 percentage points. The average acceptance rate also increases for all driver types.
The largest increase is for full-time drivers with non-Tehran number plates, who as we know, have fewer outside options than the other groups. Hiding information increases the acceptance rate in this group by almost 3.39 percentage points. On the other hand, hiding information increases the acceptance rate for part-time drivers with Tehran number plates by only 0.45 percentage points. This group has the highest value of outside options available to them and can receive offers from Snapp, and as a result, while hiding information, they have access to more options than Tapsi.

A reason why hiding information cannot encourage drivers to accept more offers by large could be the existence of definite outside options available to drivers. By removing information and creating uncertainty for drivers about the profitability of the offer, drivers are drawn to using outside options such as finding a passenger by traditional street-hailing. Therefore, in a situation where many outside options are available to drivers, it is not possible to induce offer acceptance by hiding information from drivers. In addition, the expected value of receiving a ride offer for a driver in this scenario is reduced by 1020 Tomans, and therefore, the drivers are worse off. The results of this policy change are given in column (1) of Table A.3 in the Online Appendix.

To show the effect of having outside options, we set the value of non-random outside options to zero. In this way, each driver only benefits from its own outside option, $\epsilon_n$. Then, we compare the mode of hiding full information and giving full information. In the absence of outside options, hiding full information increases the average acceptance rate by 4.5 percentage points compared to the mode of providing full information. Therefore, it can be said that the reason drivers are reluctant to accept offers is the access to outside options, and if drivers do not have a variety of outside options available, hiding information can increase the acceptance rate of offers more.

We also consider four other scenarios, namely the scenario of 1) hiding the price, 2) hiding the destination and showing the price and length of the ride, 3) hiding the price and destination, and 4) hiding the destination and length of the ride. In all these cases the average acceptance rate does not show much change. The results of these policies are summarized in columns (2)-(5) in Table A.3. As it turns out, hiding information in all possible scenarios reduces the expected value of being online in Tapsi and the expected value of receiving a ride offer (rows (3) and (4) in Table A.3, respectively). Also, Tapsi’s expected revenue from sending an offer to a driver (row (2) in Table A.3) does not change largely in any of the scenarios. To calculate this revenue, we consider the following intuition: If an offer is rejected, the income of Tapsi will be zero. On the other hand, if the driver accepts the ride, a fraction of the price paid by the passenger will be given to Tapsi as a commission. Therefore, the expected Tapsi revenue from sending an offer to a driver is the weighted average of the commission resulting from the accepted trips. This income is approximately equal to 400 Tomans if full information is given to the driver. Table A.3 shows the amount of change in this revenue in each scenario relative to the mode of showing full information to drivers.

In interpreting the results, we should note that in Iran, traditional street-hailing is possible for any vehicle, whereas in other countries, only licensed taxis can pick up passengers in this way. Therefore, drivers of companies like Uber have little choice to work with their cars other than working in Uber. But drivers working in Tapsi can easily switch between traditional and online modes. Therefore, creating uncertainty in the profitability of the online mode cannot encourage them to accept much more ride offers.

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8 Since by showing the destination, the driver can estimate the length of the ride, we leave out the scenario of showing the destination and hiding the length of the ride.
6.2  Imposing Fines in the Form of Delay in Receiving the Next Offer

Another way to persuade drivers to accept offers is to impose fines for rejecting an offer. One way to impose a penalty is to delay receiving a ride offer for drivers who reject an offer. For example, if a driver does not accept an offer, the platform can stop sending them any new offers for the next ten minutes. If we take each unit of time as two minutes, then the value of an offer for driver \( n \) at location \( i \) and at time \( t \) is equal to

\[
V_{n,i,t}(p, x, j) = \max\{ (p(1 - \text{com}) - cx) + \beta_r (\max\{ u_{n,i,t+x, OP_{i,t+x} } \}) \}
\]

\[
\max\{ \beta_r OP_{n,i,t+1}, \beta_r^2 OP_{n,i,t+2}, \beta_r^3 OP_{n,i,t+3}, \beta_r^4 OP_{n,i,t+4}, \beta_r^5 \max\{ u_{n,i,t+5, OP_{n,i,t+5} } \} \}
\]

where \( u_{n,i,t} \) has the same definition as in Error! Reference source not found.. Note that in equation (2), we assumed the driver would continue working with probability \( \beta_r \) in the next period if they do not receive an offer in the current period. Similarly, here, the probability of wanting to continue working in the next period while not receiving an offer in the current period is \( \beta_r \), and \( \beta_r^k \) is the probability of being willing to work after \( k \) periods of not receiving any offers. The results of this policy are given in column (1) of Table A.4. A comparison of the average acceptance rate in this case with the no-penalty case shows that the imposition of a 10-minute delay penalty increases the acceptance rate by only about 0.07 percentage points. This very small amount indicates that the reason for the low average acceptance rate of drivers is their opportunity to receive outside options and the imposition of fines cannot greatly increase their acceptance rate. Additionally, this policy does not largely change the expected revenue of Tapsi and the welfare of drivers in the form of the expected value of receiving a ride offer and the value of being online in Tapsi (rows (3) and (4) in column (1) of Table A.4 in the Online Appendix, respectively).

6.3  Imposing Fines in the Form of Reducing the Likelihood of Receiving the Next Offer

To encourage drivers to accept more offers, the platform can reduce the likelihood of receiving the next offer for drivers who have rejected an offer. For example, the probability of receiving an offer for a driver who has rejected their last offer can be cut to half of the probability of receiving an offer for a driver who has accepted the previous offer. In this case, the value of an offer for driver \( n \) at origin \( i \) and time \( t \) will be

\[
V_{n,i,t}(p, x, j) = \max\{ (p(1 - \text{com}) - cx) + \beta_r (\max\{ u_{n,i,t+x, OP_{n,i,t+x} } \}) \beta_r \max\{ u_{n,i,t+1, OP_{n,i,t+1} } \} \}
\]

in which,

\[
u_{n,k,t}^{\text{Nor}} = \mathbb{E}_{p', x', j'}[V_{n,k,t}(p', x', j')]\mathbb{P}_{k,t} + [\beta_r \max\{ u_{n,k,t+1, OP_{n,k,t+1} } \}](1 - \mathbb{P}_{k,t})
\]

\[
u_{n,k,t}^{\text{Pun}} = \mathbb{E}_{p', x', j'}[V_{n,k,t}(p', x', j')]\mathbb{P}_{k,t}^{\text{Pun}} + [\beta_r \max\{ u_{n,k,t+1, OP_{n,k,t+1} } \}](1 - \mathbb{P}_{k,t}^{\text{Pun}})
\]
and we have

$$P_{\text{pun}} = 0.5P$$  \hspace{1cm} (18)

$$E[V_{n,k,t}(p',x',j')] \equiv \Sigma_{(p',x',j')}f_{k,t}(p',x',j')V_{n,k,t}(p',x',j')$$  \hspace{1cm} (19)

The results of this policy are presented in Table A.4. Imposing such a penalty increases the average acceptance rate by 0.9 percentage points. This increase indicates that the acceptance rate can be slightly increased by reducing the likelihood of receiving the next offer upon rejection. This policy does not greatly change the expected revenue of Tapsi and the welfare of drivers in the form of the expected value of receiving a ride offer and the value of being online in Tapsi (rows (3) and (4) in column (2) of Table A.4 respectively). The slight increase in the acceptance rate is also a reminder that drivers working in Tapsi have low acceptance rates due to the numerous outside options available to them.

### 6.4 Changing the Tapsi Commission

Another scenario is a change in the Tapsi commission rate, which is directly related to the price that drivers receive from accepting an offer. As Figure A.8 in the Online Appendix shows, when the rate of the Tapsi commission increases, the acceptance rate of drivers decreases. In contrast, as the Tapsi commission rate decreases, the acceptance rate of offers increases. However, this increase is still small. For example, if the Tapsi commission rate is reduced from 15% to 5%, the acceptance rate increases by about two percentage points. Also, as the commission rate decreases, both the welfare of drivers in terms of the value of being online in Tapsi and the value of receiving an offer increase (Figure A.9 in the Online Appendix); But the amount of the increase in welfare is also small.

A change in Tapsi’s commission rate also affects the platform’s expected revenue. The elasticity of Tapsi’s revenue relative to a 1% change from the current commission rate (15%) is about 0.009. This means that as the commission rate decreases, Tapsi’s expected revenue from sending an offer to a driver decreases. Therefore, it is not possible to increase Tapsi’s expected revenue by reducing the Tapsi commission. This could be because with a 1% reduction in the commission rate, the acceptance rate increases by only 0.02 percentage points, which is not a large amount.

### 6.5 Discussion of the Results of the Counterfactual Policies

An examination of the various cases of hiding information and the imposition of fines for rejecting offers shows that these policies cannot greatly increase the average driver acceptance rate, in the presence of varied outside options. Thus, the reason for the low acceptance rate of Tapsi drivers is the low net profitability of rides compared to the outside options available to drivers. Drivers can usually pick up passengers in the traditional way. This option is not available to drivers working for companies such as Uber and in countries where it is not possible to find passengers easily by street-hailing. Therefore, given the circumstances, it is not possible to largely increase the acceptance rate by hiding information and imposing rejection fines.
To demonstrate the importance of the profitability of ride offers relative to the value of outside options, we examine the effect of increasing the price, other factors being the same. Figure A.10 in the Online Appendix shows that the acceptance rate increases as the price increases; for example, if prices increase by 50%, the average acceptance rate increases by about 8 percentage points. Therefore, other factors being the same, the acceptance rate can be increased by increasing the profitability of offers. As changes in price affect the demand, the demand elasticity would determine whether the policy of increasing the price raises Tapsi’s profit or not.

7 Conclusion

Platforms operating in ride-hailing markets aim to match drivers and passengers in a way that they can find each other instantly, by forwarding passengers’ ride requests to nearby drivers. Upon receiving a ride offer, drivers must decide whether to accept it or not. A low acceptance rate by drivers leads to friction in the matching process. To solve this problem, some platforms encourage drivers to accept offers by hiding ride information from drivers or imposing fines in case of rejecting offers.

In this paper, we used a novel micro-level dataset with details of ride requests registered in Tapsi, one of the largest ride-hailing companies in Iran/Middle East, to find quantitative answers to the crucial question of how different policies regarding the amount of ride information shared with the drivers or imposition of penalties for rejecting offers can affect matching efficiency and the company’s revenue. At the time of forwarding a request to a driver, Tapsi discloses all ride information to the driver, and the driver is free to accept or reject the offer at no cost. We model the driver’s decision using a quantitative stochastic discrete dynamic programming model, in which, in order to accept or reject an offer, drivers compare the value of each offer including the discounted value in the destination, with the value of available outside options and the value of waiting for better options. Using the Tapsi dataset, we matched the simulated moments obtained from this model to those of the data and estimated the dynamic model parameters using the Simulated Method of Moments estimation method. We then tested the model and ran counterfactual analysis to quantitatively evaluate the impact of different policies. In particular, we used 64 moments including the weighted average acceptance rate of offers for any type of driver (4 types), from any origin to any destination (4 modes), on weekdays, Thursdays, and Fridays, between 4 a.m. and 11:59 p.m. (48 moments) and the weighted average acceptance rate by type of driver, from any origin to any destination, between 12 a.m. and 3:59 a.m. (16 moments).

We find that what leads to a low driver acceptance rate in Tapsi is the existence of a variety of outside options available to drivers. Therefore, concealing information or imposing fines on drivers who reject offers cannot greatly encourage drivers to accept more offers. In addition, these policies do not change the welfare of the drivers or the income of Tapsi to a large extent. Other factors being constant, price increases can raise the acceptance rate of offers because, in this way, the profitability of rides increases compared to outside options.

There are some limitations to our analysis. First, we have taken demand as exogenous to the model. Further studies can endogenize demand and inspect how it might be affected by a higher acceptance rate. In addition, in evaluating the counterfactuals, we did not consider the effect of changing the platform’s policies on drivers’ decision to quit the platform and work in other ride-hailing platforms that exist and provide full information to drivers. Incorporating the competition between existing platforms and their strategies to attract more drivers by providing them with more information and more authority in making their decisions could be the subject of future research.
References


Figures:

Figure 1: Mean of Relative Number of Requests over Hours of Day on Weekdays and Weekends

![Figure 1](image1.png)

Note: Figure shows the mean of the relative number of requests in each hour of the day for weekdays and weekends, along with the 95% confidence interval. The relative number of requests is defined as the number of requests normalized to the mean number of rides in each hour of each day available in the data. The relative number of requests is used to maintain data confidentiality.

Figure 2: Relative Acceptance Rate of Drivers over Hours of Day on Weekdays and Weekends

![Figure 2](image2.png)

Note: Figure shows the relative acceptance rate in each hour of the day for weekdays and weekends, along with the 95% confidence interval. The relative acceptance rate is defined as the percentage of offers accepted by drivers in each hour of the day over
weekdays or weekends, divided by the percentage of all accepted offers in the data. The relative acceptance rate is used to maintain data confidentiality.

Figure 3: Relative Rate of No-Driver-Found Requests over Hours of Day on Weekdays and Weekends

Note: Figure shows the relative rate of requests that end up with no drivers found for them in each hour of the day for weekdays and weekends, along with the 95% confidence interval. The relative rate of no-drivers-found requests is defined as the percentage of requests with no drivers found for them in each hour of the day over weekdays or weekends, divided by the percentage of all such requests in the data. The relative rate is used to maintain data confidentiality.
Figure 4: Mean of Relative Waiting Time over Hours of Day on Weekdays and Weekends

![Figure 4: Mean of Relative Waiting Time over Hours of Day on Weekdays and Weekends](image)

Note: Figure shows the mean of the relative waiting time for a request to be accepted, along with the 95% confidence interval. The relative waiting time is defined as the time interval between when a ride request is submitted and when it is assigned to a driver, divided by the mean of this time interval in the data. The relative time interval is used to maintain data confidentiality.

Figure 5: Comparing the Number of Requests and Acceptance Rate in 256 Regions of Tehran

(a) Distribution of Ride Requests Registered in each of Tehran's 256 Regions

![Figure 5: Comparing the Number of Requests and Acceptance Rate in 256 Regions of Tehran](image)
(b) Distribution of Acceptance Rate in each of Tehran’s 256 Regions

Figure 6: Relative Acceptance Rate of Drivers by type of Number Plate over Hours of Day on Weekdays and Weekends

Note: Figure shows the relative acceptance rate for drivers with vehicles having Tehran and non-Tehran number plates in each hour of the day for weekdays (left) and weekends (right), along with the 95% confidence interval. The relative acceptance rate is defined as the percentage of offers accepted by drivers in each hour of the day over weekdays or weekends, divided by the percentage of all offers accepted in the data. The relative acceptance rate is used to maintain data confidentiality.
Figure 7: Relative Acceptance Rate Based on Price per Length (in Minutes) of the Ride

Note: Figure shows the relative acceptance rate per every minute of the length of ride, along with the 95% confidence interval. The length of the ride is calculated as the sum of the expected passenger-driver distance and origin-destination distance. The relative acceptance rate is defined as the percentage of offers accepted by drivers in each price per minute category, divided by the percentage of all offers accepted in the data. The relative acceptance rate is used to maintain data confidentiality.
Description: To maintain data confidentiality, the values are normalized to the total acceptance rate in the data.
## Tables:

Table 1: Estimated Values for Parameters

<table>
<thead>
<tr>
<th>Parameters in Price Unit</th>
<th>Estimated Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>0.069***</td>
<td>The cost of driving for each unit of time is 69 Tomans.</td>
</tr>
<tr>
<td></td>
<td>(0.1968)</td>
<td></td>
</tr>
<tr>
<td>$op_{plate=tehran}$</td>
<td>4.320***</td>
<td>The value of outside options for drivers with Tehran number plates is 4320 Tomans higher compared to non-Tehran number plate drivers, in each working period.</td>
</tr>
<tr>
<td></td>
<td>(0.1631)</td>
<td></td>
</tr>
<tr>
<td>$op_{type=fulltime}$</td>
<td>-21.259***</td>
<td>The value of outside options for full-time drivers is 21259 Tomans less compared to part-time drivers, in each working period.</td>
</tr>
<tr>
<td></td>
<td>(0.0936)</td>
<td></td>
</tr>
<tr>
<td>$op_{dow=thursday}$</td>
<td>-2.976***</td>
<td>The value of outside options in each working period on Thursdays is 2976 Tomans less than on working days.</td>
</tr>
<tr>
<td></td>
<td>(0.2873)</td>
<td></td>
</tr>
<tr>
<td>$op_{dow=friday}$</td>
<td>-4.692***</td>
<td>The value of outside options in each working period on Fridays is 4692 Tomans less than on working days.</td>
</tr>
<tr>
<td></td>
<td>(0.4750)</td>
<td></td>
</tr>
<tr>
<td>$op_{k=center}$</td>
<td>37.786***</td>
<td>The value of outside options in each working period in the center of Tehran is 37786 Tomans.</td>
</tr>
<tr>
<td></td>
<td>0.2822</td>
<td></td>
</tr>
<tr>
<td>$op_{k=out}$</td>
<td>36.923***</td>
<td>The value of outside options in each working period in non-central areas of Tehran is 36923 Tomans.</td>
</tr>
<tr>
<td></td>
<td>(0.0754)</td>
<td></td>
</tr>
<tr>
<td>$op_{e(day)}$</td>
<td>8.110***</td>
<td>The value of outside options in each working period is 8110 Tomans more during the day than at midnight.</td>
</tr>
<tr>
<td></td>
<td>(0.4438)</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>27.915***</td>
<td>The standard deviation for the value of outside options is equal to 27915 Tomans in each working period.</td>
</tr>
<tr>
<td></td>
<td>(0.0980)</td>
<td></td>
</tr>
</tbody>
</table>

### Other Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimated Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_a$</td>
<td>0.1854***</td>
<td>A driver will continue to work after completing a trip with an 18.54% chance.</td>
</tr>
<tr>
<td></td>
<td>0.1757</td>
<td></td>
</tr>
<tr>
<td>$\beta_r$</td>
<td>0.8364***</td>
<td>A driver will continue to work with an 83.64% probability after rejecting a ride offer.</td>
</tr>
<tr>
<td></td>
<td>0.1076</td>
<td></td>
</tr>
</tbody>
</table>

### Functions

<table>
<thead>
<tr>
<th>Functions</th>
<th>Estimated Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V$</td>
<td>33.749</td>
<td>The average value of receiving an offer for each driver is 33749 Tomans in each working period.</td>
</tr>
<tr>
<td>$U$</td>
<td>32.360</td>
<td>The value of being online in the Tapsi application is on average 32360 Tomans for each driver in each working period.</td>
</tr>
</tbody>
</table>

Description: Estimated values for the parameters are obtained using the SMM method by considering 4000 simulations. The values in parentheses indicate the standard deviation of the estimates. Each price unit for parameters estimated in column (2) is equal to 1000 Tomans. The significance level at 1 percent is indicated by ***. The variances are obtained using Nelder and Mead (1995) method, by taking the absolute value of the diagonal of the variance-covariance matrix to avoid measurement errors resulting in negative variances. The value of being online in the Tapsi application is equal to the expected value for a driver who is online and is waiting to receive a ride offer. The value of receiving a ride offer is the value for a driver who now has a ride offer and must decide whether to accept or reject it. A working period corresponds to consecutive time intervals that the driver works constantly, without taking a rest. Note that the daily minimum wage was around 34,000 Tomans on average during the period of our study.
Appendix

Proof of the Formula for Calculating $\mathbb{P}$

As mentioned in section (3), the probability of receiving an offer at each origin and each time, $\mathbb{P}$ depends on three different factors: the number of requests ($r$), the number of online drivers ($o$), and the average number of drivers that receive the offer ($m$). The probability that a given driver receives an offer is equal to

$$\frac{m}{o}$$

and therefore, the probability that the driver will not receive this offer is equal to

$$1 - \frac{m}{o}$$

The probability that the driver receives no offer is thus

$$\left(1 - \frac{m}{o}\right)^r$$

And therefore, the probability that the driver will receive an offer will be

$$\mathbb{P}_{k,t} = 1 - \left(1 - \frac{m}{o}\right)^r$$