Investigating the Relocation Behavior of Ride-sourcing Drivers

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SHORT SUMMARY

In the business model of ride-sourcing platforms, drivers are individual service suppliers offering door-to-door transport services to riders. Drivers freely adopt their own relocation strategies including waiting, cruising freely, or following the platform recommendations. These decisions can substantially impact the balance between supply and demand, and consequently affect system performance such as match rate, empty mileage, and traffic congestion. To this end, we conducted a stated choice experiment to investigate the searching behavior of ride-sourcing drivers in the current system setting and examine novel policies. A unique dataset of 576 ride-sourcing drivers working in the US was collected and a choice modeling approach was used. The results suggest that ride-sourcing drivers' relocation strategies significantly vary between different groups of drivers depending on their employment status, working experience, daily operations, among others. We discuss the implications of our findings for various platform policies on real-time information sharing and platform repositioning guidance.

Keywords: *discrete choice modeling, drivers' behavior, ride-sourcing, shared mobility.*

1. INTRODUCTION

Ride-sourcing is a digital two-sided platform that matches ride requests submitted by riders via a mobile app with available drivers who supply a door-to-door transport service. In this setting, drivers are not only chauffeurs but also private fleet providers. At the operational level, drivers can independently decide on whether to wait around the drop-off location of the last rider, drive to the areas recommended by the platform, or cruise freely with the aim of finding a ride request. This freedom has fundamental implications for the system performance in general and the balance between supply and demand in particular. For instance, the unavailability of drivers in a certain region can increase the rider's waiting time and decrease the match rate, and consequently the system reliability. Furthermore, the so-called idle cruising - referring to moving while no passenger is in the car - can contribute to traffic congestion caused by ride-sourcing operations (Tirachini, 2020).

Ride-sourcing platforms are interested in steering individual suppliers so as to keep the balance between supply and demand. This is a complex task due to the unpredictable nature of the dynamic demand and the heterogeneity among service suppliers. Platforms adopt various dispatching algorithms, initiatives, and pricing strategies to efficiently reposition empty vehicles and possibly reduce the fleet size and total vehicle mileage. Despite all the implemented strategies, there still exist serious challenges and counterproductive results such as a high number of idle vehicles, increasing empty mileage, and traffic congestion (Tirachini, 2020). The mainstream of the literature is focused on the optimal algorithms and assumes that the drivers are fully compliant with the repositioning algorithms and policies of a centralized platform and ignore the behavioral aspects of individual drivers. There is a growing body of literature aiming to explore the behavior of ride-sourcing drivers in various aspects (Zuniga-Garcia et al., 2020; Ashkrof et al., 2021). Ashkrof et al. (2020) carried out a qualitative analysis of system operations from the drivers' perspective and proposed a framework that maps the relationship between the tactical and operational decisions of drivers. Analyzing 9000 ride-sourcing trips in Beijing, Leng et al. (2016) found out that the idle time of drivers is reduced when a set of financial incentives are offered by the platform. Using trajectory information of the DiDi drivers in China, Xu et al. (2020) reported clear customer search behavioral differences at various time of the day, especially between full-time and part-time drivers.

To the best of our knowledge, this is the first study that is specifically designed to empirically investigate drivers' relocation strategies and their reaction to the platform repositioning guidance. Furthermore, we also study drivers' responses to potential alternative policies and related information provisioned. The findings offer deep insights for platform providers, algorithm developers, policymakers, and other researchers in this field to facilitate the improvement of system operations and planning.

2. METHODOLOGY

To investigate the relocation strategies of ride-sourcing drivers, a Stated Choice (SC) experiment is designed. In this study, we consider the choice situation occurring when a driver has recently completed a ride and is searching for a new passenger. Therefore, four relocation alternatives are defined:

- Staying as close as possible to the current location.
- Driving to a surge area where surge pricing occurs due to a local high imbalance between supply and demand.
- Driving to a high-demand area where the demand is expected to be high while the trip fare remains at the normal rate.
- Cruising freely into a different area based on the driver's experience, preferences, or gut feelings.

The choice is first made based upon a set of existing attributes that drivers currently experience with existing ride-sourcing systems. Subsequently, some currently unavailable information and incentives are added to investigate their potential implications in the relocation choice. Figure 1 illustrates the experiment set-up employed in this study.

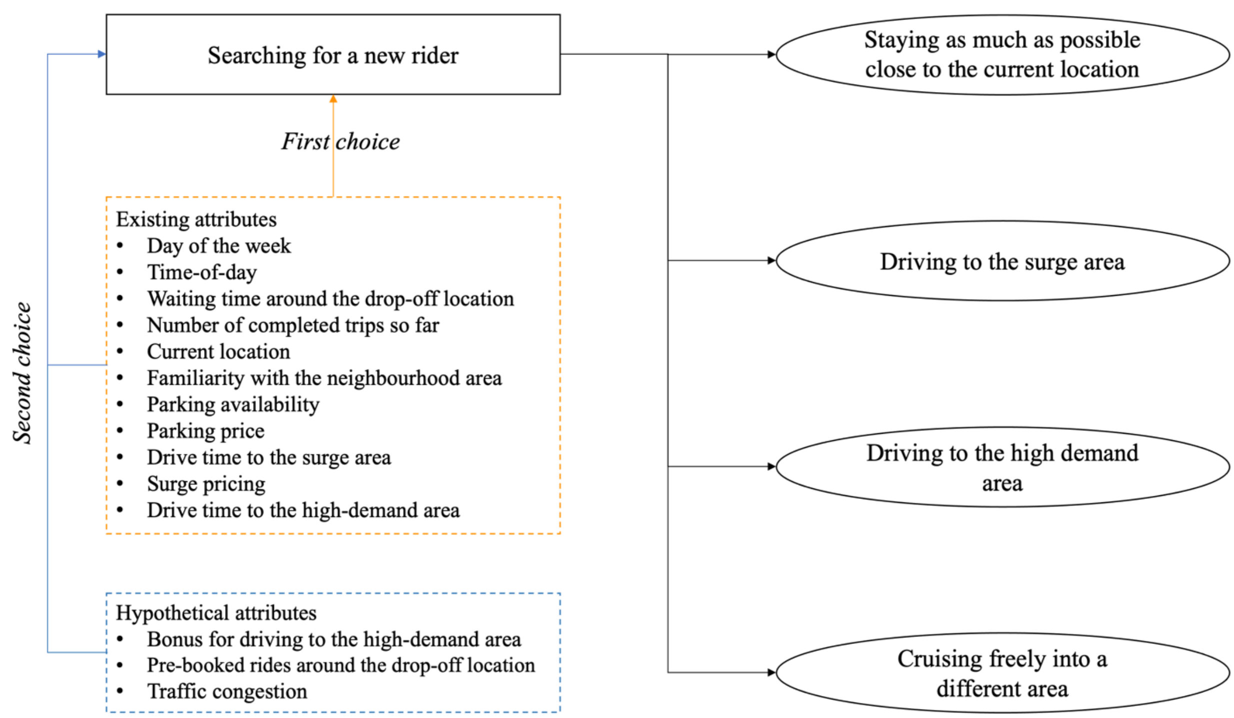

Figure 1: The stated choice experiment set-up

To design the SC experiment with a statistically efficient combination of the attribute levels, a Bayesian efficient design is applied. The software package NGENE was used to construct 24 choice sets in 6 blocks that were randomly distributed between respondents. A survey software platform is used to program an online questionnaire that enables the data collection process. Figure 2 provides an illustration of the choice set displayed in each scenario.

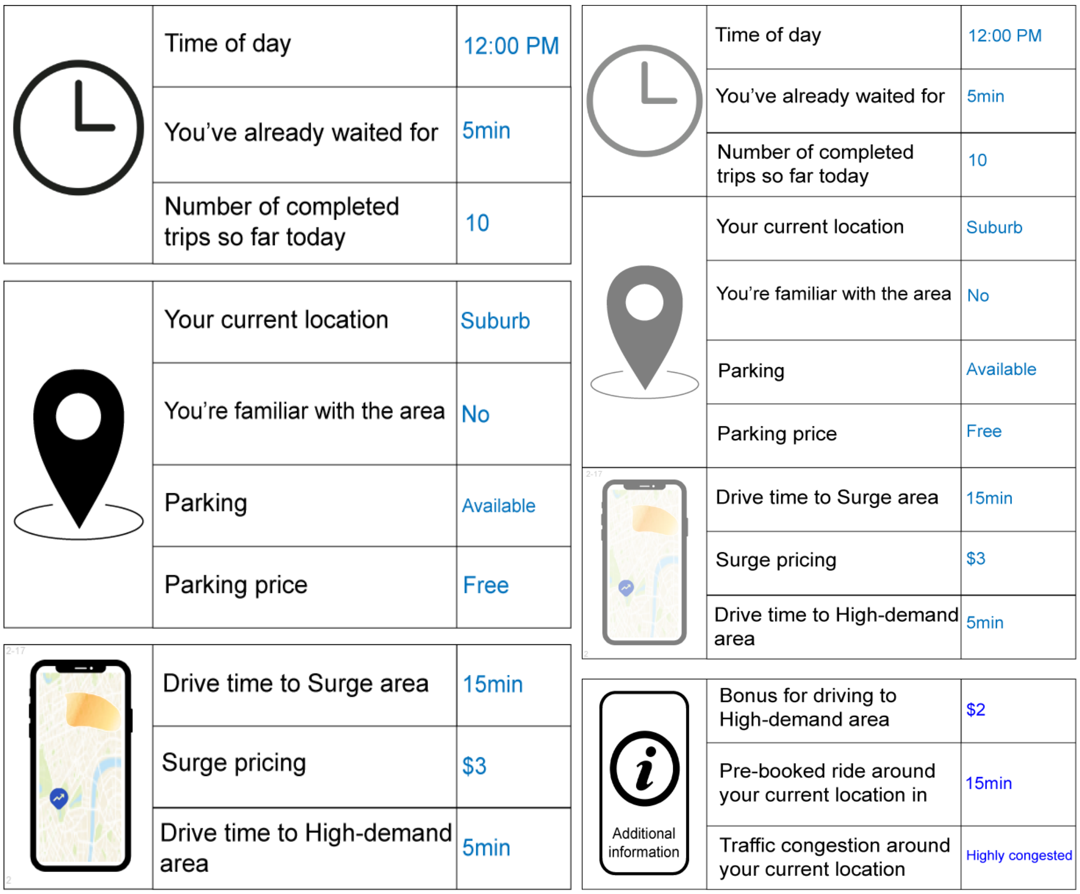

Figure 2: Choice set interface with the existing (left) and hypothetical (right) attributes

A discrete choice modeling approach is applied to unravel the relocation strategies of drivers and identify the influential existing and potential factors. The utility function of alternative j is formulated as follows:

$$U_j = \sum_{k=1}^{K} \beta_{jk}.x_{jk} + \sum_{m=1}^{M} \beta_m.x_m + \varepsilon_j \quad (1)$$

Where the first term refers to the alternative-specific attributes (x_{jk}) presented in the choice experiment, and the second component includes the individual-specific factors such as the driver's socio-economic characteristics (x_m). The last component is the error term (ε_j) that captures the unexplained variation under the assumption of being independently and identically distributed. β_{jk} and β_m are the coefficients vectors representing the marginal effects of the exploratory attributes and individual-specific factors, respectively. The Random Utility Maximation (RUM) approach is used to estimate the choice models by the software package PandasBiogeme (Bierlaire, 2020).

3. RESULTS

In this study, Uber and Lyft drivers working in the US were selected to be part of the survey sample. A panel company was hired to recruit prospective respondents for this hard-to-reach target group. In total, 752 complete responses were collected between November 2020 and February 2021. A comprehensive data quality analysis was performed to filter out low-quality responses caused by short response time and the lack of sufficient attention. As a result, 576 responses were retained for the analysis.

Table 1 shows the results of the models built upon the existing and hypothetical attributes. ASC represents the alternative specific constant, B is the estimated coefficient, and the suffixes W (Waiting/staying around), S (driving to the Surge area), H (driving to the High-demand area), and C (Cruising freely) indicate the utility function for which the attribute is relevant.

Table 1: The results of the choice models built upon the existing and the hypothetical attributes

Parameters	**Scenario 1** (only existing attributes)	**Scenario 2** (with hypothetical attributes)
ASC_Waiting	-0.283	0.988***
B_Waiting_Time_W [min]	-0.019**	-0.017**
B_Working_on_Weekend_Friday_W	0.427***	0.236*
B_Working_Shift_C [1=Beginning of the shift]	-0.583***	-
B_Number_of_Trips_S&H	0.060***	0.048***
B_Location_W [1=City center]	0.315**	-0.022
B_Parking_Availability_W [1=Available]	0.277**	0.325**
B_Familiarity_with_Neighborhood_C [1=Familiar]	-0.201	-0.334*
B_Surge_Pricing_S [$]	0.190***	0.166***
B_Driving_Time_to_Surge_Area_S [min]	-0.020***	-0.017*
B_Driving_Time_to_High-Demand_area_H [min]	-0.037***	-0.042***
B_Taxi_Driving_Experience_C [1=Taxi driver]	-0.478***	-0.370**
B_Fully_Satisfied_Drivers_H [1=Fully satisfied]	0.371***	0.524***
B_Beginners_W&C [1=Beginners]	-0.322**	-0.018
B_Part-time_drivers_W [1=Part-time]	0.393***	-
B_High_Acceptance_Rate_W [1=Acceptance rate>70%]	-0.407***	-0.369***
B_Educated_Driver_W [1=Educated]	0.406***	0.003
B_Working_Shift_W [1=Beginning of the shift]	-	-0.344**
B_Part-Time_Drivers_C [1=Part-time]	-	-0.326**
B_Pre-Booked_Rides_W [min]	-	-0.020*
B_Bonus_to_Drive_to_High-Demand_Area_H [$]	-	0.177***
B_Traffic_Congestion_C [1= Highly congested]	-	-0.283*
Initial Log-Likelihood	**-3194.022**	**-3194.022**
Final Log-Likelihood	**-2938.735**	**-2949.844**
McFadden's pseudo R-squared	**0.080**	**0.076**
AIC	**5911.471**	**5939.687**
BIC	**6009.092**	**6054.536**

*Significance code: *p-value<0.05, **p-value<0.01, ***p-value<0.001*

We first review the results of the models estimated for the current information display settings and then proceed with reporting the results of the hypothetical scenario. The negative value of B_Waiting_Time_W suggests that drivers tend to move to a different area in case the waiting time around the drop-off location increases. On the other hand, drivers working on weekends or Fridays are inclined to wait around their location. This might stem from the relatively higher demand on these days of the week. Therefore, drivers can receive more requests with less driving effort (operational costs). Based on the current system setting, at the beginning of the shift, there is a strong aversion to cruise freely. This might be because the risks of self-determining movements are typically higher, therefore, drivers are willing to first try out waiting or following the platform's suggestions. Interestingly, drivers who have had the experience of being conventional taxi drivers prior to joining the platform dislike cruising on their own. This could be attributed to their experience in cruising as taxi drivers, leading them to opt for a system that offers more guidance.

The number of completed trips since the beginning of the shift has a positive effect on driving to the surge and high-demand areas. A satisfactory working experience can develop trust between drivers and the platform which leads to a higher willingness to follow the app recommendation. This is in line with the positive significant value of B_Fully_Satisfied_Driver_H that suggests that highly satisfied drivers (i.e., the drivers who gave 4.5/5 out of 5 stars to the system performance) are more likely to drive to a high-demand area indicated by the platform. Moreover, beginning drivers with a working experience of less than one year prefer not to wait or cruise freely but drive to the surge and high-demand areas.

The chance of staying close to the current location is higher in the city center where the probability of receiving a ride while standing still or driving around is higher compared to a suburban area. Parking availability is also a crucial factor that motivates drivers to wait at a particular location to receive a new ride request. Another influential determinant is the employment status of drivers. Part-time drivers tend to stay around. They need to minimize their operational costs during their working time which is limited by other working activities. Drivers who have a college degree or higher are also more inclined to wait, everything else being the same. Drivers with an acceptance rate of more than 70% tend to move as opposed to waiting. These drivers are less selective in assessing ride requests and their intention is to find a ride as quickly as possible, paying less attention to its attractiveness.

As expected, surge pricing stimulates drivers to head to the surge area as they can expect to earn more money in the case of reaching the designated area. On the other hand, a higher distance to a surge or a high-demand area discourages drivers to follow the platform repositioning suggestions. This is because the demand-supply intensity dynamically changes and the risk of missing the opportunity is higher when the distance increases. The value of drive to the surge area which is the amount of surge pricing for every minute added to the travel time to the surge area is estimated to be roughly 0.11 $/min based on the results. In the second scenario where more information is shown to drivers, a strong unobserved preference for staying around is identified. Moreover, being familiar with the neighborhood area increases the probability of waiting or driving to the surge or high-demand area. Presumably, this familiarity helps drivers to find suitable spots to wait or choose the best route to promptly reach the surge or high-demand area. The existence of pre-booked rides around the drop-off location can influence the choice of drivers to stay around. This hypothetical attribute gives drivers information about the next potential client who can be picked up within their current zone. If drivers declare their interest in waiting for the incoming request, the ride will be secured for them. Nevertheless, drivers may prefer not to stay if the waiting time is relatively high. Moreover, drivers are more likely not to wait at the beginning of the shift arguably because alternative promotions including surge pricing and high-demand bonus can be expected.

Another variable included in the second scenario is the bonus for driving to a high-demand area. The positive significant value of the estimated parameter suggests that drivers are highly inclined to reach the high-demand area if a promotion is offered. Traffic congestion around the current location turns out to be a significant determinant. A highly congested area discourages drivers to cruise freely given that they probably get stuck in the traffic congestion without picking up passengers – increasing the operational costs.

Due to the more restricted time, part-time drivers are less inclined to cruise freely and are more responsive to financial promotions and extra information offered by the platform than full-time drivers, everything else being equal.

4. CONCLUSIONS

We empirically study the relocation behavior of ride-sourcing drivers. To this end, we designed a stated choice experiment to allow investigating the behavior of drivers under the existing system settings as well as under a hypothetical scenario exploring their potential responses in the event of new circumstances. In total, 576 qualified responses from Uber and Lyft drivers working in the US were collected, and a series of discrete choice models were estimated. Four choice alternatives were considered: driving to a surge area, driving to a high-demand area, staying around the drop-off location, and cruising freely. Various existing and hypothetical incentives and information about driving conditions and demand characteristics were shared with drivers to identify the influential determinants and their potential effects. We also investigated the impacts of other aspects of driver's behavior at the tactical level (working shift) and the operational level (ride acceptance behavior) as well as other individual attributes.

Our findings suggest that following the surge and high-demand area appears to be more attractive for some groups of drivers depending on their working experience, operational performances, and satisfaction level. Namely, relatively inexperienced drivers, as well as highly satisfied drivers, and drivers with a higher number of completed trips since the beginning of their shift are more likely to follow the recommended areas. The level of surge pricing and the expected travel time between the driver's location and the surge/high-demand area are recognized as the other significant determinants.

Additional repositioning guidance options which are not yet available were studied in the hypothetical scenario. Drivers were given a second chance based on some additional information including the existence of any pre-booked rides in the waiting area (associated with the waiting alternative), bonus for driving to the high-demand area, and the level of congestion around their location (which may impact propensity for cruising freely). We found all of these variables can play a role in the relocation choice of drivers. Pre-booked rides can be shown to drivers in advance to enable them to assess whether to stay or not depending on the expected waiting time. In order to motivate drivers to relocate to a particular area such as a high-demand area, a guaranteed bonus may be offered. This guaranteed bonus is valued 60% more highly than surge pricing which is not necessarily secured. These results suggest that platform guidance policy may be extended to assist drivers in making more informed decisions and thus possibly improve the level of service, reduce deadhead movements, and improve the wider acceptability of ride-sourcing services.

The findings can be used to consider the underlying determinants of drivers' behavior in predicting their relocation choices and designing tailored drivers' incentives. For instance, educated part-time drivers with high acceptance rate who are more likely to stay around can be provided with more information about available parking spots and pre-booked rides in the vicinity, especially when working in the city center on weekends and Fridays. In contrast, beginning drivers are more willing to respond to detailed information about surge and high-demand areas. Given that trust between individual suppliers and the platform is key in the success of such an interactive business model (Özer et al., 2018), the information shared by the platform needs to be accurate and unbiased and communicated in real-time to build the basic trust and develop it over time.

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