Using Field Experiments to Infer Cross-Side Network Effects in the Ride-Sharing Market: How Does Driver Supply Impact Rider Orders, Cancellations, and Customer Lifetime Value?

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Abstract

In the sharing economy, how do changes in supply impact demand? We study this question by collaborating with a ride-sharing platform to conduct a natural field experiment. Our experimental design employs an instrumental variable strategy: by exogenously manipulating the driver subsidy schedule, we use the subsidy as an instrumental variable to identify the cross-side network effects of driver supply on orders, cancellations, and the aggregate customer lifetime value (CLV) of users. The results show that increasing the number of drivers at work by 1% will increase the number of customer orders by 2.01% and, conditional on the orders, further reduce the cancellation rate by 0.48%. The results also imply a long-term impact on the future revenue and profitability of the platform. We find that, for a 1% increase in the number of drivers working in the afternoon or at night, the aggregate CLV of users will increase by 1.62% or 0.50%, respectively. Our findings can help platforms improve operations, adjust incentives for suppliers, and strengthen the user experience.

1 Introduction

The past decade has witnessed the growth of the sharing economy in various industries, including transportation (e.g., Uber and Lyft), accommodation (e.g., Airbnb), and second-hand sales and personal help (e.g., Craigslist). A recent report projected that the total market value of the sharing economy would grow to $335 billion by 2025.[1] The success of sharing platforms relies on the right balance of supply and demand. A shortage on the supply side can hurt the user experience and thus negatively impact the demand side. This issue is particularly critical for the sharing economy because, unlike traditional industries, sharing platforms typically offer high flexibility for suppliers' participation decisions (Chen et al., 2019). While providing convenience for suppliers, such flexibility leads to large supply volatility and thus affects users. As an example, data from Airbnb suggest that 42% of guest requests are rejected by hosts, with congestion cited as the most important reason, and rejected guests are 40% less likely to complete any transaction (Fradkin, 2017). Such issues will have a direct impact not only on platforms' short-term performance metrics but also on their long-term profitability. As an illustration, after Lyft revealed it was having difficulty hiring drivers due to the slow recovery of the labor market after the pandemic, its stock price (which reflects investors' predictions of the company's long-term returns) dropped by 27% in a single day (Reuters, 2022). Therefore, it is essential for sharing platforms to understand the effect of supply changes on the demand side, which will help them improve their operations to ensure the right level of service for customers. This can include increasing or decreasing the number of suppliers on the platform and adjusting prices and incentives. By making data-driven decisions based on the relationship between supply and demand, platforms can reduce costs, increase profit, enhance the user experience, and ultimately stay competitive in the market.

The goal of this paper is to study the impacts of changes in supply on demand, a type of *cross-side network effects* in the literature, and thus the platform profit in the sharing

[1] https://www.pwc.com/us/en/technology/publications/assets/pwc-consumer-intelligence-series-the-sharing-economy.pdf. Accessed on March 19, 2022.

economy. Using a ride-sharing platform as our empirical context, we focus on how changes in driver supply influence users' order requests and request cancellations. While order cancellations are directly related to poor service, which will cause dissatisfaction among users, changes in order requests can be an indirect indicator of customer satisfaction when users need the service (e.g., they are less likely to make requests if the estimated pick-up time is long). Since customer (dis)satisfaction can have long-term impacts on business, we adopt an approach from the well-developed customer relationship management (CRM) literature (e.g., Schmittlein et al. 1987). Specifically, we measure the value that the driver contributes to the platform. Measuring driver value can help the platform better understand the profit impact of acquiring new drivers or losing existing drivers.

A popular approach in the CRM literature is to measure customer lifetime value (CLV), or the discounted value of the profit stream a customer brings to the business over her "lifetime" (e.g., Fader et al. 2005). This method however does not apply to calculating the value of suppliers in the sharing economy, since suppliers can be substitutes or complements, depending on how they may affect the demand. When there are plenty of suppliers relative to demand, adding one more supplier may only cannibalize demand for other suppliers, which does not benefit platforms. In contrast, when there is a supply shortage, increasing suppliers may lead to market expansion, and the demand for existing suppliers may actually increase. Instead of calculating the profit flow each driver brings to the platform, we note that driver value comes from better satisfying user needs and thus increasing demand on the platform. Our approach is to use the estimated cross-side network effect to evaluate how the aggregate CLV of all existing users is impacted by the change in driver supply on the platform. This helps us correctly measure the impact of increasing or decreasing drivers on the long-term profit of the platform.

Identifying the cross-side network effect is an essential component for measuring driver value. It has been well-studied in the marketing and economics literature; however, prior studies that investigate the effect of supply on demand mostly use observational data (e.g., Rysman, 2004; Chu and Manchanda, 2016; Cullen and Farronat, 2021). This approach is subject to causality concerns. There may exist unobserved factors that simultaneously impact demand and supply on platforms, and the two-sided nature of platforms suggests that supply and demand can influence each other simultaneously. Because of these issues, it is challenging to establish a causal effect using observational data.

Field experiments can effectively establish causal effects. In an ideal experiment, platforms would randomly assign users to treatment and control conditions to test how users' choices vary at different levels of supply. Such random assignment is usually impossible to implement in reality. Alternatively, platforms may manipulate the number of suppliers in different time periods and use such exogenous variations to estimate their impacts on demand. However, doing so will impose restrictions on the decisions of suppliers and cause unnatural responses from suppliers; consequently, the causal inference could be biased. To overcome this challenge, we collaborate with a ride-sharing platform to design and conduct a unique field experiment based on the idea of using instrumental variables (IVs). We offer different levels of subsidies within the range of $0 to $6 per complete trip across time slots. We set different subsidies for trips that occur in the afternoon (12p.m. to 5p.m.) and at night (6p.m. to 11p.m.) as well as on different days of the week. Unlike standard field experiments, which directly manipulate the level of treatments (i.e., how many drivers are at work in each time slot) and who participates under each treatment condition (i.e., who is at work), these are drivers' endogenous decisions in our experiment. The manipulation of subsidies is used as an IV that induces the supply change. Based on this, we can infer the impacts of supply change on demand.

Given that the average fee paid to drivers on the platform is $14, the subsidy variation is substantial enough to change the willingness of drivers to work for each hour. Therefore, the subsidy changes satisfy the *relevance* condition as an IV for driver supply. When designing the subsidy schedule, we as researchers lack information on the factors that may affect the demand in each time slot; as a result, the subsidy changes also satisfy the *exogeneity* condition for IVs.

To obtain a valid IV for the experimental design, several other important requirements need to be met. First, the *exclusion restriction* condition has to be satisfied in the experimental design. Although the exclusion restriction is generally the same as the exogeneity condition, in our experimental design, the requirement is that the introduction of IVs (i.e., subsidies) does not lead to a new demand shifter in the experiment. Second, our experiment has to be *natural* so that subjects (i.e., drivers) react to experimental manipulations in a natural way, ensuring the external validity and generalizability of our findings (Al-Ubaydli and List, 2013). Finally, to help separate the effects of driver supply from time-specific demand effects, the subsidy schedule has to be *balanced* across time slots. We will discuss in detail how, before running the field experiment, we ensure that the experimental design satisfies those requirements.

With subsidies as the IV, we employ the two-stage least-square (2SLS) regressions to estimate how driver supply changes cause rider[2] orders and cancellations to vary. The estimation results show that a 1% increase in drivers' supply can lead to a 2.01% increase in riders' order requests, indicating a large cross-side network effect. We also find that, conditional on riders making a request, the probability that riders cancel their orders reduces by 0.45% with a 1% increase in drivers. The results are robust under alternative model specifications. We argue that the high order and cancellation elasticities are driven by the predicted and actual waiting time for riders. When a rider opens the APP, she can see the number of available drivers nearby and the time needed for the nearest driver to reach the origination location. A larger number of drivers nearby will encourage the rider to make a ride request and complete the trip.

Because users typically have repeated needs for the service, higher driver supply can not only increase the immediate number of orders but also have a positive long-term impact on the platform. We combine the estimation results with additional estimations of the impact of cancellations on repeated usages and customer attrition to calculate how the aggregate CLV of drivers changes with the increase of drivers at work, either by new hiring or

[2] "Users" refer to individuals who have registered at the platform for ride services in future, and "riders" refer to those users who have a need for the ride service.

incentivizing existing drivers to work longer, in different time periods. We find that increasing driver supply in the afternoon by 1% will increase the aggregate CLV by 1.624%. However, the aggregate CLV will only increase by 0.501% if those added drivers work at night. The results suggest that the value of customer acquisition for the platform is different depending on the work-time preference of drivers.

Understanding cross-side network effects has important substantive implications for sharing platforms. The results can help platforms and their investors better predict the long-term profit impact on the business (e.g., how the aggregate CLV of users changes) of macro socioeconomic shocks in the labor market (e.g., a labor shortage after the pandemic). Platforms can also use the results to adjust prices charged to users and incentives offered to suppliers for a better balance of demand and supply. Although this study is not centered on the effectiveness of subsidies, we use data from the experiment to show how the car-sharing platform can use our findings to optimize driver subsidies. We find that the platform would incur a loss in the aggregate CLV by offering the same subsidies as an incentive to all drivers and that the higher the subsidy level is, the larger the loss will be. This is because without subsidies, the platform's revenues from each trip are already low. However, we find that *active* and *inactive* drivers react to monetary incentives in a different way across time slots. The platform's aggregate CLV will increase by 8.80% by offering \$1 subsidy to active drivers in afternoons and the same amount of subsidy for inactive drivers at nights, for both weekdays and weekends. Furthermore, we further show that the number of orders and the total revenue per driver will increase by 5.65% and 21.51%, respectively, under the \$1 subsidy. These results suggest that drivers on the platform are *complements* with one another, as the increase in the number of drivers will make current drivers at work better off.

Our research contributes to the literature by employing a field experiment to quantify the cross-side network effects of supply on demand and using the results to measure driver value. From a methodology perspective, we make two contributions. First, we show how to measure the value of suppliers in the sharing economy. Instead of directly measuring the profit flow from each supplier, we propose measuring the cross-side effect under supplier acquisition or attrition; based on that, we evaluate the impact on the aggregate CLV of users. Second, firms and researchers can use our experimental design with the embedded IV approach when direct randomization of subjects into treatment and control conditions is infeasible. Although past literature (e.g., Duflo 2004) suggests that treatment assignments can be used as an instrument in the presence of non-compliance issues, researchers have not specifically designed instrumental variables in experiments. We also highlight the importance of making sure that other conditions, including the exclusion restriction, naturalness, and external validity, are satisfied in the experimental design.

2 Literature Review

Our study is directly related to the literature that examines network effects on two-sided platforms. Network effects refer to the phenomenon that the participation of one side of platforms can impact the participation of the same side or the other side (Rysman 2009). Previous empirical studies have relied primarily on observational data to estimate network effects. Rysman (2004) estimates the network effect between advertisers and consumers of Yellow Pages and shows that a competitive market with multiple Yellow Pages is better for social welfare than a monopoly market. Yao and Mela (2008) model the behavior of buyers and sellers on an online auction platform and show how changes in the number of participants on one side of the platform affect participants' behavior on the other side. Using a natural experiment on Wikipedia, Zhang and Zhu (2011) find that a decrease in audience size can lower the contribution of content providers on the platform. On an online commerce platform, Chu and Manchanda (2016) show that the number of sellers has a large impact on the number of buyers. Farronato et al. (2020) also find that the supply increase on a pet-sitting platform can increase demand due to network effects. However, using TaskRabbit data, Cullen and Farronato (2021) examine matching efficiency and find no evidence that an increase in sellers or buyers can improve matching efficiency.

Identifying the causal relationship for network effects using observational data is challenging. To the best of our knowledge, two marketing studies have used field experiments: Tucker and Zhang (2011) manipulate the information provided for sellers regarding the number of existing sellers and buyers to investigate the impact on suppliers. They find that information on a large number of buyers can lead to an increase in supply. In a field experiment on a dating app, Fong (2022) varies information about the number of potential matches and competitors shown to users. She finds that more potential matches make users more selective, whereas more competitors make users less selective. Both papers manipulate the beliefs of participants or the information available to them but do not actually change the levels of supply or demand. In contrast, we implement a field experiment that varies supply, which enables us to quantify how demand responds to actual changes in supply.

Our paper is also related to an emerging literature that studies the sharing economy in general. Prior research has investigated several important issues related to supply and demand on sharing platforms. On the supply side, prior literature has investigated how unemployment encourages suppliers' participation (Huang et al., 2020), racial and sexual identity discrimination (Cui et al., 2020; Mejia and Parker, 2021), and pricing frictions and the adoption of pricing tools (Li et al. 2016; Zhang et al., 2022). Farronato and Fradkin (2022) demonstrate that the entry of Airbnb can improve consumers' welfare, especially in a high-demand period (e.g., New Year) and area (New York City) when traditional hotels cannot flexibly increase room supply. On the demand side, previous studies have examined demand seasonality (Li and Srinivasan, 2019; Farronato and Fradkin, 2022) and reviewed writing in response to various incentives (Fradkin et al., 2021; Zervas et al., 2021). Several papers further investigate the spillover effects of sharing platforms on other industries, including the impact of Airbnb on housing and rental prices (Horn and Merante, 2017; Barron et al., 2021) and hotel revenue (Zervas et al., 2017), and the impact of Uber on the demand for public transportation (Babar, Y., & Burtch, 2020; Pan and Qiu, 2022), household bankruptcy (Nian et al., 2020), service quality in restaurants (Shin et al., 2022), and sexual assault (Park et al., 2021). We enrich this stream of research by examining the impact of supply on demand on sharing economy platforms using a field experiment.

The approach to measuring driver value is related to the well-established CRM marketing literature (Schmittlein et al. 1987; Fader et al. 2005). Because of complicated network or spillover effects, the CLV of a customer cannot be directly measured by the profit flow the customer contributes. Several previous studies have addressed this problem. Wu et al. (2011), for example, measure the CLV of customers acquired from Google search advertising when there are spillover effects on offline customer acquisitions. They show a significant difference if spillover effects are ignored. Several other studies specifically studied the value of customers when same-side network effects exist. As examples, using the network of cellular users, Nitzan and Libai (2011),Ascarza et al. (2017), and Hu et al. (2019) show that the usage and churn of a focal customer can increase the usage and churn probability of connected customers, suggesting that both positive and negative spillover effects exist among customers' networks. Stourm and Stourm (2023) measure the effect of customer acquisition on a sharing platform when there are substitution and strategic pricing effects among suppliers. Finally, Chen and Mehta (2023) measure the "social" CLV of gym users when same-side network externalities exist among users. They demonstrate a big difference between the "social" CLV and "private" CLV when measuring the direct revenue flow of each gym user without accounting for externalities. Our goal of measuring driver value on the ride-sharing platform is similar to the above studies; however, we use a very different approach by focusing on the cross-side network effect. Furthermore, while most studies rely on observational data (one exception is Ascarza et al. 2017), we use a novel field experiment. Our study has a cleaner and stronger identification of causal network effects.

Finally, we study the effect of driver supply on rider cancellations. This is related to a large stream of literature on service failure. Previous research has demonstrated that service failure can trigger customers' frustration and thus reduce their satisfaction and repeat purchases (Hess Jr et al., 2003; Magnini et al., 2007; Gelbrich, 2010). Various strategies have been identified to mitigate the negative consequences of service failure, such as direct compensation (Grewal et al., 2008; Cohen et al., 2021), co-creation of recovery (Roggeveen et al., 2012), and leveraging existing customer relationships (DeWitt and Brady, 2003). Most of the prior studies focus on service failure in the offline context. Given that sharing platforms have revolutionized the service industry, our study of how the lack of supply leads to service failure on the platforms makes a novel contribution to this research stream.

3 Empirical Setting and Field Experiment

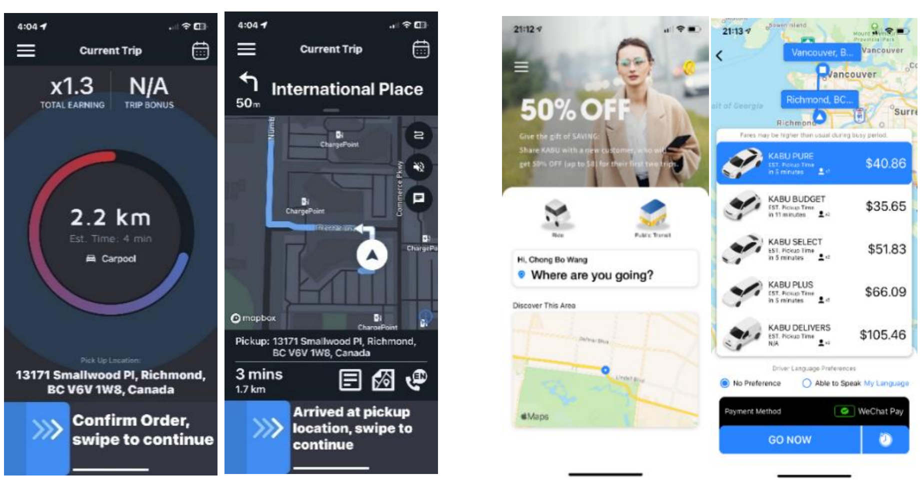
We conducted the field experiment in collaboration with a ride-sharing platform that operates in Vancouver, Canada. We will first introduce the empirical setting, then describe the experimental design. Finally, we will provide data statistics.

3.1 Empirical Setting

The operation of the platform is similar to other ride-sharing companies such as Uber and Lyft. On the supply side, drivers voluntarily join the platform and have full discretion over their schedules. In our empirical analysis, we define drivers' work as the time when they are online on the platform's app, as this indicates they are either driving riders or available to pick up riders. Drivers' income comes from the share of the trip fee paid by riders. The trip fee is determined by the distance, duration, and time of the trip. Drivers keep 80% of the trip fee, and the remaining 20% goes to the platform. Drivers also have to pay a fixed fee to the platform for each completed order. The platform occasionally offers subsidies at certain hours and days to encourage drivers to work when it anticipates high demand. The subsidy is a lump sum payment for each completed trip.

On the demand side, riders can conveniently request a trip from the app. When riders open the app, they first specify their origination and destination locations. Next, they are shown available drivers within an 8-km radius and the time it would take for the nearest driver to reach the origination location. After that, they can submit a request for a ride. If a rider sees that no drivers are close by and/or that it would take the nearest one a long time to arrive, they may leave the app and choose other type of transportation, and the platform will not receive the order.[3] If the rider orders a ride, the request will be sent to drivers who are not currently driving riders, with priority given to the closest driver. A driver receiving the request has 60 seconds to accept or reject it. If the driver rejects the order or 60 seconds have passed, the request will be redirected to another driver. The rider can cancel the trip before any driver accepts the request or after a driver has accepted and the wait grows too long for the rider.

Two features of the order and pick-up process are important for our field experiment. First, when a driver sees the ride request, they have the origination information but not the destination. Therefore, it is unlikely that the driver can strategically wait and pick trips that might be more profitable. Second, although the driver and rider may use text messages from the app to exchange information (e.g., to clarify the pickup location or let the rider know when the vehicle will arrive), there is very limited room for the driver to provide any other services, such as helping load the luggage, before the rider is picked up. This suggests that the rider's order and cancel decisions are unlikely to be affected by the driver's service. We show the interface of the app for both drivers and riders in Figure 1.



Drivers Riders

Figure 1. The App Interface

[3] Henceforth, we use "order" and "request" interchangeably in our discussion irrespective of whether the request is accepted by a driver or not.

The platform reveals that trip cancellations have a large negative impact on its profit and drivers' income. We find from the data that the average cancel rate is 24%,[4] implying a very significant revenue loss for the platform. We find that 99% of cancellations are initiated by riders.[5] Since cancellations often result from riders waiting for too long for a driver to accept their order or to arrive, the high cancellation rate indicates a bad service experience that could lead to customer dissatisfaction. This, in turn, may affect their future riding choices.

3.2 Experimental Design

We conducted a field experiment to investigate the impact of driver supply on user demand. Ideally, we would randomize the number of drivers at work in each time slot. Such an experimental design, however, is infeasible, as drivers decide when and how long they will work. Even if the platform could determine each driver's work hours, such a design would distort outcomes by forcing drivers' choices. For instance, drivers assigned to an undesirable hour might choose not to accept orders; therefore, a high number of drivers would not necessarily imply a high level of actual supply. Furthermore, drivers might behave differently if they were aware they were under study. For instance, they might work harder due to the experimenter demand effect (Zizzo, 2010; Quidt et al., 2018). This would bias the causal inference and keep the results from generalizing to a real business setting.

To tackle this problem, we base our novel experimental design on the idea of using instrumental variables (IVs) and vary subsidies for drivers across time periods. Unlike standard field experiments, which directly manipulate the level of treatments (i.e., how many drivers are at work in each period), in our design, drivers make their own work-hour decisions. Subsidies are used as an IV that induces the number of drivers at work in each hour.

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[4] We combine multiple cancellations from the same rider within a short time into one cancellation because these cancellations reflect a single usage need from the rider.

[5] While a driver can cancel the trip after acceptance, this is rare, as the platform penalizes them heavily for cancellation.

Our experimental period lasts four weeks, from June 20 to July 17, 2021. There are three levels of subsidies in the first three weeks: \$2, \$4, or \$6 for each afternoon (from 12:00p.m. to 5:59p.m.) trip, and \$0, \$3, or \$5 for each night (from 6:00p.m. to 11:59p.m.) trip.[6] We group the days of each week into Monday to Thursday, Friday to Saturday, and Sunday, and offer different subsidies for each group of days. For afternoon or night trips in each group of days, we rotate the three subsidy levels across weeks. The first three panels of Table 1 show the detailed subsidy schedule from Week 1 to Week 3. Note that in each time slot (afternoon or night of each group of days), each subsidy level is offered exactly once each week. Since the subsidy schedule for the first three weeks is balanced, the schedule for the fourth week is simplified, with only \$0, \$4 and \$5 offered across time slots (see the lower right panel of Table 1). Because the experiment controls the subsidy levels in the afternoon and night, our subsequent empirical analysis will not use observations between 12:00a.m. and 12:00p.m.

Table 1. Subsidy Schedule (\$ Per Completed Trip)

	Week 1			Week 2		
	Mon.-Thu.	Fri.-Sat.	Sun.	Mon.-Thu.	Fri.-Sat.	Sun.
Afternoon	6	2	4	2	4	6
Night	0	5	3	3	0	5
	Week 3			Week 4		
	Mon.-Thu.	Fri.-Sat.	Sun.	Mon.-Thu.	Fri.-Sat.	Sun.
Afternoon	4	6	2	4	5	5
Night	5	3	0	0	0	5

Previous research has shown that drivers' decisions about working on a ride-sharing platform crucially depend on the tradeoff between the expected return from the platform

[6] The average subsidy level in the afternoon is higher than at night because of the platform's request. However, we make sure that on some days during the experiment, the subsidy at night is higher than the subsidy in the afternoon. We also control for the hour-of-the-day fixed effects in regressions. More details can be found in the next section.

and the expected return from other work options (Crawford and Meng, 2011; Chen et al., 2019). On the ride-sharing platform, the average trip fee fare paid by riders is around $21. On average, $15 of the trip fare will be distributed to the drivers, and the platform earns the remaining $6 per trip without subsidy. The subsidy level in our experiment (from $2 to $6) is economically important from the perspective of drivers and the platform. Therefore, the subsidy changes satisfy the *relevance* condition as an IV for driver supply.[7] Further, when designing the subsidy schedule, we lack information on how demand may fluctuate each hour throughout the experimental period; as such, the subsidy changes also satisfy the *exogeneity* condition for IVs.

It is important that our experimental design also satisfies the *exclusion restriction* condition. That is, the introduction of subsidies will not create a new demand shifter in the experiment. Our first concern is that, with a higher level of subsidy, drivers may offer a better service and, as such, it will directly shift the demand. If this is the case, we cannot disentangle the effect of a larger driver supply and the effect of a better service on demand. The unique feature that drivers cannot provide services before picking up riders (except for text/call communications on the exact pickup location and timing) ensures that the latter effect is unlikely to directly influence riders' order and cancel decisions, which are the focused outcome variables of our empirical analysis. In addition, we make sure that riders are not aware that drivers receive subsidies in the experiment; thus, their order and cancel decisions are not affected by the variation of subsidies, except through changes in the number of drivers available nearby.[8] Overall, we believe that our experimental design satisfies the exclusion restriction.

[7] Note that monetary incentives are particularly effective in the sharing economy, as drivers decide when to work. In contrast, the work schedule for taxi drivers is usually fixed; thus, monetary incentive may not satisfy the relevance condition.

[8] One may be concerned that, if drivers provide better services (after pickup) under higher subsidies, riders may expect a better service in future and thus their future order and cancel decisions may be different. However, our experiment only runs for four weeks. As riders do not take rides on a frequent basis (on average, once a week), we do not believe this will have a substantial effect. Also note that the subsidy level varies over time; as such, the effect on riders' expectations is not always positive.

Our experiment also has to satisfy the *naturalness* condition—i.e., riders and drivers need to react to the experiment in a natural way to ensure the external validity and generalizability of our findings (Al-Ubaydli and List, 2013). Because riders are not aware of the subsidies offered to drivers, there should not be any unnatural responses from riders' order and cancel decisions. Since the platform has used subsidies in the past as an incentive for drivers, our experimental manipulation is thus embedded in the regular operation of the platform. As such, during the experiment, drivers are unlikely to be aware that they are under study. We are also concerned that, since the subsidy is allotted on a per trip basis, drivers may react to a higher subsidy by strategically choosing shorter trips when deciding whether or not to accept a trip request. However, since drivers do not receive destination information before accepting trip requests, and cancellations initiated by drivers are very rare in the data, we conclude that this should not be a concern. Our setting, therefore, is a natural field experiment that occurs in an environment in which subjects (drivers and riders) react to experimental manipulations in a natural way.

Finally, to separate the effects of driver supply from time-specific demand effects, it is important that the subsidy schedule is *balanced* across time slots. To achieve a balanced design, we rotate the subsidy levels across weeks. In the afternoons or nights of each group of days, each subsidy level is offered exactly once in each week in each time slot (see Table 1). Further, the average subsidy for afternoon or night trips is identical across the first three weeks (i.e., the average is \$4 for an afternoon trip and \$2.67 for a night trip in each week). With this balanced design, we are able to include hour, day-of-week, and week fixed effects in our empirical analysis (more details in the next section) to separate the time-specific demand effects.

3.2.1 A Manipulation Check

Our experimental design varies subsidies to influence driver supply. For the experiment to work, the number of drivers at work has to react to the change in subsidy levels. To test whether this is the case, we counted the number of drivers working each hour during the first three weeks of our experiment.[9] We use a regression approach to separate out several fixed effects, including week, day of the week, and hour of day (from 12p.m. to 11p.m.). We then calculate the average residual of the number of drivers at each subsidy level to test the relationship. We do so for the afternoon and night separately. We plot the average residual number of drivers for different levels of subsidy and the corresponding 90% confidence interval in Figure 5. This exercise is equivalent to a manipulation check for field experiments.

Figure 2 shows a clear positive relationship between subsidy and drivers at work in the afternoon: while the average residual of the number of drivers is negative at the $2 subsidy level, it is significantly positive at the $6 subsidy. However, drivers' supply is less sensitive to subsidies at night. While the average residual of the number of drivers is positive at the $5 subsidy, it is negative at the $3 subsidy, even lower than that at the $0 subsidy, although they are not significantly different from zero. The lack of a significant difference is likely due to lower demand at night than in the afternoon, which reduces the effectiveness of the subsidy as a monetary incentive for drivers.

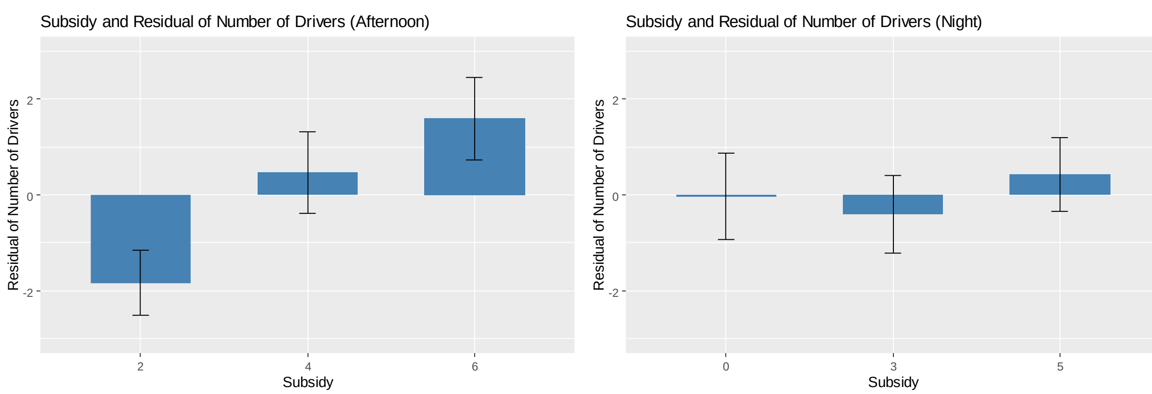

Figure 2. The Relationship between Subsidy and Drivers at Work

Although the manipulation test shows mixed results for night hours, overall, we believe subsidies can motivate drivers to work. We will further use regressions to show that subsidies pass the test of weak instrument in the next section. This is important, since the

[9] We do not include the last week, as the subsidy schedule is not as balanced as during the first three weeks.

goal of manipulating the subsidy level in our experiment is to create an instrument for drivers at work.

3.3 Data Statistics

The platform provides a granular dataset that includes supply and demand information for all drivers and riders. In total, our data covers 198 unique drivers, 2,337 unique users, and 7,152 trips. The subsidy schedule was announced in the middle of the first day of the experiment (June 20). Since drivers may have been unaware of the subsidy schedule when they made work decisions, we exclude observations of that day in our analysis.

On the supply side, the data is at the driver-shift level, such that we can observe when each driver starts or stops working. If a driver is online anytime during an hour, we count that driver as working during that hour. On the demand side, our data is at the rider-order level. An order is defined as the event of a rider making a request for a ride. For each order, a complete trip means that a driver accepts the order, picks up the rider, and drops off the rider at the destination. An incomplete trip means that the order was cancelled by the rider. The data also shows the request time and pick-up time for a complete trip, or the cancellation time for an incomplete trip. As such, we can calculate the waiting time for both types of trips. In addition, we also know the time of the driver's confirmation.

Furthermore, we observe for each order the trip status (i.e., completed or cancelled), trip distance and duration, fare, subsidy, and the GPS coordinates of the pickup and drop-off locations. From the data, we construct two major outcome variables. The first is the total number of orders (including complete or incomplete trips) in each hour, and the second is whether the order is cancelled or not.

We provide data statistics related to the study below. We first look at driver supply. Drivers did not work for 38% of driver-week combinations. Conditional on the driver working for the week, Figure 3 shows the distribution of the number of weekly work hours of drivers. The majority of drivers work fewer than 30 hours. The red line in the figure indicates that the average weekly hours worked is 23. These numbers suggest most drivers are driving for the platform on a part-time basis. The figure also shows a large variation in drivers' work hours. For example, while about 43% of drivers work for less than 10 hours a week, about 15% work for more than 50 hours. The pattern shows the flexibility of work decisions on the ride-sharing platform.

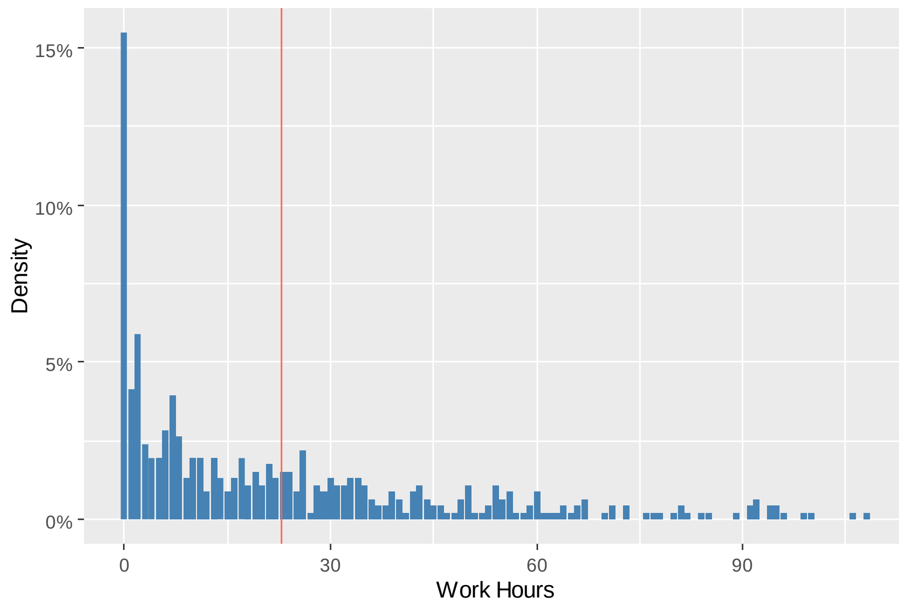

Figure 3. Drivers' Weekly Work Hour Distribution

To further understand the heterogeneity in work hours among drivers, we classify drivers into active and inactive types. We calculate the total work hours of each driver for two months before our experiment starts, and categorize drivers as active if their work hours are above the median and as inactive otherwise. We then break a week into six time slots (Monday-Thursday afternoon, Monday-Thursday night, Friday-Sunday afternoon, Friday-Sunday night, Sunday afternoon, and Sunday night). We further define Monday to Thursday as a weekday and Friday to Saturday as a weekend. Sunday is defined as a separate category because it is a transition from high demand on the weekend to relatively low demand on Monday. We then show the average work hours by driver types and time slots in Table 2. As expected, active drivers work almost ten times longer than inactive drivers. Interestingly, active and inactive drivers have different preferences for when to work. Active drivers work more in the afternoon, which likely suggests they treat working on the platform as a full-time job and thus drive more during regular working hours. While inactive drivers also work more on weekday afternoons, they prefer to work longer at night on weekends and Sundays. This is probably because nighttime and weekends are non-regular working hours and thus are more preferred by inactive drivers for whom the work is a part-time job.

Table 2. Average Work Minutes by Driver Type and Time Slot

	Active Drivers			Inactive Drivers		
	Mon.-Thu.	Fri.-Sat.	Sun.	Mon.-Thu.	Fri.-Sat.	Sun.
Afternoon	70.33	83.85	72.99	6.45	6.95	4.14
Night	61.87	77.65	62.44	5.81	7.91	5.29

Note: The numbers represent drivers' average work minutes for corresponding time slots.

Figure 4 shows the average number of working drivers and riders, and the average cancel rate at each hour of the day (starting from 12p.m. until 11:59p.m.) during the experiment. For the sake of data confidentiality, we subtract the variables from their means. The figure shows several interesting patterns. First, there is a positive correlation between drivers' supply and riders' demand. Specifically, the number of drivers at work and the number of riders peak between 3p.m. and 4p.m. Of course, such a correlation does not imply causal effects, and, even when they do exist, the effects can be bi-directional. Second, the changes in supply and demand are not totally aligned with each other. For example, relative to the number of riders, there are fewer drivers available from 4 to 5p.m. when the demand peaks, but there are more drivers from 7 to 9p.m., during which time demand has dropped. This probably indicates that the seriousness of the supply issue varies across hours. Finally, the purple line in the figure indicates riders' cancel rate. The rate is higher at night than in the afternoon, although the demand at night is lower. This perhaps implies that, because it is easier to find drivers (including those who work for other platforms) at night, riders may simply cancel the order and switch to Uber or Lyft if they have to wait for drivers to accept their orders or arrive to pick them up.

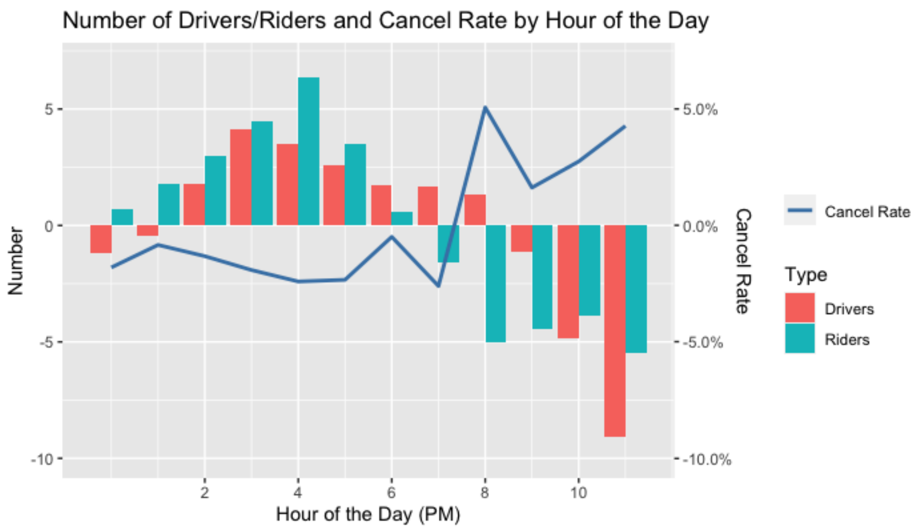

Figure 4. Supply, Demand, and Cancel Rate by Hour of the Day

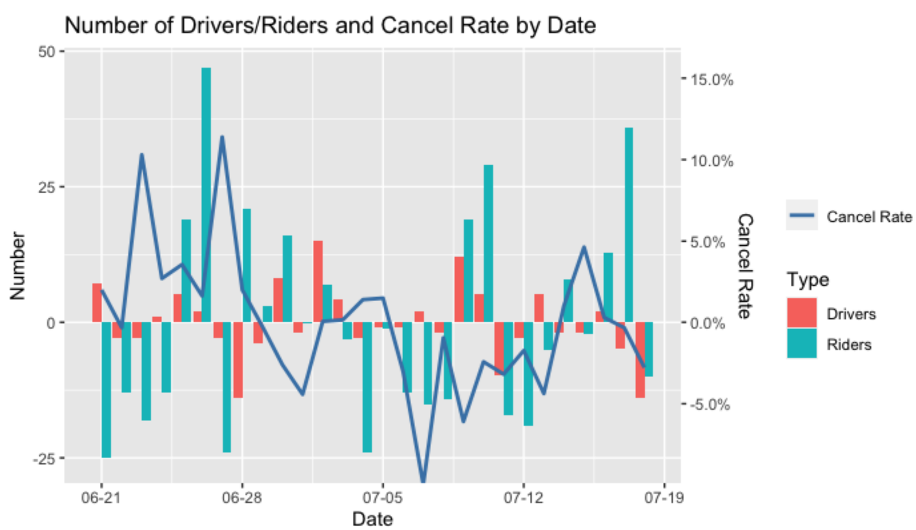

Figure 5. Daily Supply, Demand, and Cancel Rate throughout the Experiment

Figure 4 compares supply, demand, and the cancel rate by hours. Figure 5 further compares them at the daily level during our experiment period. We also subtract each variable from the mean to maintain data confidentiality. The figure shows a large misalignment between the changes in supply and demand. For example, during the first week of the experiment (from June 21 to June 28), the number of riders fluctuates significantly either below or above the average level, whereas the number of drivers is relatively stable around the average level. When the demand change is larger than the supply change, the cancel rate in general also changes correspondingly. For example, for dates around July 5, the number of drivers is close to average, but the number of riders is mostly below the average, which is associated with a low cancel rate. This suggests the importance of balancing demand and supply to prevent cancellations and improve riders' usage experience.

Table 3. Summary Statistics

		Mean	SD	Min	Max
Demand	*Completed Trips:*				
	Duration (seconds)	879	542	44	3,382
	Distance (meters)	8,549	6,956	100	52,154
	Fare ($)	21	11	6	95
	Waiting Time before Request Acceptance (seconds)	50	105	2	2,819
	Waiting Time before Pickup (seconds)	638	406	2	5,301
	Incomplete Trips:				
	Waiting Time before Cancellation (seconds)	592	2,181	30	29,423
Supply	Daily Work Hours	1.29	2.60	0	12
	Proportion of Afternoon Work Hours	52%	32%	0%	100%
	Proportion of Night Work Hours	48%	32%	0%	100%
	Proportion of Mon-Thu Work Hours	54%	30%	0%	100%
	Proportion of Fri-Sat Work Hours	35%	29%	0%	100%
	Proportion of Sun Work Hours	11%	15%	0%	100%
	Hourly Orders	0.25	0.55	0	4
	Hourly Income of Drivers ($)	11.75	8.56	0.53	54.91

Finally, Table 3 provides the summary statistics for some important data variables. On the demand side, Table 3 shows that the waiting time before pickup is about 10 minutes, on average, which is quite long relative to the average trip duration (driving time after pickup). For incomplete trips, the waiting time before the rider cancels the order is also about 10 minutes. These numbers suggest that waiting time is a problem for the platform, which will likely cause cancellations. On the supply side, we show drivers' work hours allocation within a day and across days within a week. The average daily work length of drivers is only 1.29 hours, indicating that for most drivers, this is just a part-time job. Drivers work more in the afternoon than at night, and more on weekdays than during weekends and Sundays. Finally, a driver, on average, takes one order every four hours, and the average income of the driver is $11.75 per hour.[10]

4 Regressions and Results

We report the empirical analysis results in this section. We will first discuss the regression models used in the analysis. Next, we will report the first-stage regression results and then the second-stage results, which illustrate the causal effects of driver supply on riders' orders and cancel decisions. We will also discuss the underlying mechanism driving these findings.

4.1 2SLS Regressions

To estimate the effects of driver supply on demand, we use the following regressions:

$$\log(Total\ Order_t + 1) = \alpha_1 * \log(Total\ Driver_t + 1) + \delta_{t1} + \sigma_{t1} + \varphi_{t1} + e_{t1}, \quad (1)$$

$$Cancel_{it} = \alpha_2 * log(Total\ Driver_t + 1) + \delta_{t2} + \sigma_{t2} + \varphi_{t2} + e_{it2}. \quad (2)$$

where $Total\ Order_t$ is the number of orders (including complete and incomplete trips) in hour t, $Total\ Driver_t$ is the number of drivers at work in the hour, and, conditional on rider i making an order in hour t, $Cancel_{it}$ is a binary variable indicating whether or not the order is cancelled. Note that the unit of analysis of equation (1) is at the hourly level and that of equation (2) is at the order level. To control for time-varying factors that may affect the demand, we use a rich set of fixed effects, including week fixed effect δ's, day-of-week fixed effect σ's, and hour-of-the-day fixed effect φ's, in the two regressions. Finally, e_{t1} and e_{it2} are residual errors.

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[10] This is consistent with the data reported previously. For instance, Uber drivers make a median profit of US$8.55 (CA$11.46) per hour before taxes (see https://www.theguardian.com/technology/2018/mar/01/uber-lyft-driver-wages-median-report).

In equation (1), α_1 represents the cross-side network effect of driver supply on riders' order decisions. In this log-log specification, α_1 is also equivalent to the elasticity of rider orders in response to the change in driver supply. In equation (2), α_2 represents the effect of driver supply on riders' cancellation decisions after they make the order request. It is also a cross-side network effect because cancellations are a demand-side behavior that will reduce total demand on the platform. These are our focal parameters in the empirical analysis.

The cross-side network effects α_1 and α_2 are difficult to identify because of the endogeneity issue. As discussed in the Introduction, there could be unobserved factors that affect not only riders' order and cancel decisions but also drivers' work decisions. Furthermore, there is a potential simultaneity issue: as the number of orders and cancellations are a function of the number of drivers at work, the latter could also be a function of the former. Therefore, directly estimating equations (1) and (2) from observed data could lead to biased estimation results.

We use the experimental design to identify α_1 and α_2. The variation of subsidies is a valid IV for $Total\ Driver_t$ in the two regressions. Therefore, we run the two-stage least-square (2SLS) regressions. In the first stage, we run.

$$\log(Total\ Driver_t + 1) = \beta_1 * \log(Subsidy_t + 1) + \delta_t + \sigma_t + \varphi_t + e_t, \tag{3}$$

where $Subsidy_t$ is the subsidy per trip for drivers working in hour t. We also use δ_t, σ_t, and φ_t to control for the week, day-of-week, and hour-of-the-day fixed effects. After that, we use the predicted $\log(\widehat{Total\ Driver_t} + 1)$ based on the first-stage regression to replace $\log(Total\ Driver_t + 1)$ in equations (1) and (2), and run the second-stage regressions to estimate α_1 and α_2.

We note that a *balanced* subsidy schedule is important not only for creating variation in the subsidy levels across hours but also for separating the effect of subsidies from time fixed effects in equation (3). For example, while the subsidy in the afternoon from Monday to Thursday in the first week is the highest at \$6, it drops to the lowest level at \$2 in the second week (see Table 1). This helps to separate the subsidy effect from the day-of-week fixed effect. Furthermore, the subsidy levels in the afternoon or at night averaged across weekdays, weekends, and Sunday are the same in the first three weeks. This helps to separate the subsidy effect from the week fixed effect.

4.2 The Impact of Subsidy on Driver Supply

We first report the first-stage regression results. Column (1) in Table 4 shows that subsidy has a significant positive impact on the number of drivers at work. Since we take logarithmic transformation for both dependent and independent variables, the estimate suggests that a 1% increase in subsidy for each trip will increase the number of drivers working in that hour by 0.037%. We further conduct an F-test and find the F-value to be 9.08, with the corresponding p-value at 0.003. The F-value exceeds the threshold value of 8.96 suggested by Stock et al. (2002); as such, we can reject the null hypothesis that the subsidy is a weak instrument. Therefore, the relevance condition for a valid IV is satisfied.

As a robustness check, we use the expected income of drivers to replace the subsidy level in equation (3). For each hour, the expected income is calculated as the product of the expected number of orders and the sum of the expected trip fare and subsidy per trip. The expected number of orders and trip fare are the averages we calculate from data collected two months prior to the experiment. The coefficient in this specification represents the elasticity of driver supply with respect to their income, which could be a more relevant measure for researchers and ride-sharing platforms. The results are reported in Column (2) of Table 4. Consistent with our previous finding, the result suggests that a 1% increase in the expected income can increase the driver supply by 0.127%.

Table 4. The Impact Subsidy on Driver Supply

	DV: log (Total Drivers+1)	
	(1)	(2)
log (Subsidy+1)	0.037***	
	(0.012)	
log (Expected Income+1)		0.127***
		(0.046)
Week Fixed Effect	Yes	Yes
Day of Week Fixed Effect	Yes	Yes
Hour of Day Fixed Effect	Yes	Yes
Observations	324	324
R^2	0.697	0.695
Adjusted R^2	0.676	0.674

Notes: (1) the observation is at the hour level; (2) *p<0.1; **p<0.05; ***p<0.01

4.3 The Impacts of Driver Supply on Demand

In second-stage regressions, we use the predicted $\log(Total\ Driver_t + 1)$ based on the results from Table 4. To show the importance of using the instrument to infer the causal effects, we also run OLS regressions directly using the observed $\log(Total\ Driver_t + 1)$. The results are reported in Table 5.

The results in column (2) of Table 5 are based on using the subsidy as the IV for the number of drivers at work. We find that driver supply has a significant positive impact on rider demand: a 1% increase in drivers at work leads to 2.007% more rider orders on the platform. This is a very impressive result; it implies that whether or not there is a sufficient number of drivers is an important factor for riders making order decisions.

For a robustness check, we also use the results from using the expected income in the first-stage regression. Column (3) of Table 5 shows that the estimated coefficient is significantly positive, and the effect size is comparable to that in Column (2). In contrast, the OLS regression shows a negative estimate, which is statistically insignificant in Column (1), suggesting that the cross-side network effect would have been severely under-biased had our experiment not used subsidies as the instrument. Such a downward bias implies that the unobserved factors that cause a demand shock (i.e., the error term in equation (1)) are negatively correlated with the number of drivers at work. One example that explains such a negative correlation is that, on a day with nice weather, more riders would go out and need a ride. At the same time, however, more drivers would likely want to enjoy leisure time and be less likely to work on nice days. Consequently, the demand shock in equation (1) is negatively correlated with the observed number of drivers from the data. This is possible because ride-sharing drivers can choose their work hours in a flexible way. In a different context, as in the taxi industry, workers are less likely to have flexibility; as such, we are unlikely to observe such negative correlation. The striking difference between OLS and IV estimates highlights the importance of using field experiments to estimate cross-side network effects on sharing platforms.

Columns (4) to (6) presents the estimated effects of driver supply on riders' order cancellations. To implement the second-stage regressions, we first obtain the predicted number of drivers at work at the hourly level, using the results from Table 4, and then run a linear probability model. Note that, since we use the binary outcome variable of whether or not an order is canceled, the number of observations in these regressions is higher than columns (1) to (3), which are at the hourly level.

Column (5) of Table 5 suggests that increasing driver supply will reduce the cancellation probability, although the effect is only significant at the 10% level. A 1% increase in the number of drivers would reduce the order cancellation rate by 0.480%. In comparison, the OLS estimate (see column (4) of Table 5) is statistically insignificant, and its magnitude is smaller than that using the IV regression. This result implies that the unobserved factors that cause shifts in cancellations are positively correlated with the number of drivers at work. To continue with the previous example, if drivers are less likely to work on nice days, riders would find it harder to request rides from Uber or Lyft. Consequently, they will be more patient during the waiting time and less likely to cancel their orders. This explains why the error term in equation (2) is positively correlated with the observed number of drivers at work.

Table 5. The Impact of Driver Supply on Rider Demand

	DV: log (Total Orders+1)			Cancellation		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV		OLS	IV	
		Subsidy	Expected Income		Subsidy	Expected Income
log (Total Drivers+1)	-0.093	2.007**	2.647**	-0.067	-0.480*	0.210
	(0.166)	(0.967)	(1.054)	(0.045)	(0.283)	(0.302)
Week Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Hour of Day Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324	324	324	3,411	3,411	3411
R^2	0.536	0.542	0.536	0.009	0.009	0.008
Adjusted R^2	0.504	0.511	0.504	0.003	0.003	0.002

Notes: (1) the observation is at the hour level for model (1)-(3) and at the order level for model (4)-(6); (2) *p<0.1; **p<0.05; ***p<0.01.

One potential issue with the cancellation regressions is that, when we repeat the second-stage regression using the expected income as the IV for the number of drivers at work, the estimated effect is positive but statistically insignificant (see column (6) of Table 5). One possible reason for this inconsistent result is that, when using the expected income as the IV, there is less data variation in the first-stage regression; thus, the fitted R-square is lower than that obtained from using the subsidy as the IV (see the comparison of R-square in

Table 4). This can cause the estimate in the second-stage regression to be less significant. The lack of robustness in the regression results suggests we should be more careful when interpreting our findings on the impact on cancellations.[11]

4.4 An Underlying Mechanism

When we presented the findings to the platform's management, they stated that they are consistent with business operations: Before placing an order, riders can see from the app the number of available drivers within the 8-km. radius of the pickup location and the estimated time of arrival for the closest driver. Riders are more likely to place orders if there are more drivers nearby. In addition, riders have to wait for their requests to be accepted by drivers. With more drivers nearby, riders may anticipate a larger likelihood of acceptance and thus be encouraged to place orders. The underlying mechanism for the findings about the cancel rate is similar: As the number of drivers nearby increases, the time for drivers to accept requests and for riders to wait for the pickup decreases, making it less likely that riders will cancel orders. Previous research suggested that long waiting time is one of the major frustrations that causes users to stop using the service on ride-sharing platforms (Cohen et al., 2021). A shortage of drivers will increase wait times and as a result, becomes a competitive disadvantage for ride-sharing platforms.

Although we cannot directly test that the documented cross-side network effects are due to the change in riders' waiting time, we use the experiment data to find indirect evidence consistent with this mechanism. Since waiting time is truncated above for incomplete trips, we choose to focus on the waiting time for complete trips, for which we observe how long it takes for an order to be accepted by a driver and, after the order is accepted, how long it takes for the driver to come to the pickup location. We study the correlation between both the time length of an order and the number of drivers at work during the hour the order is made. Table 6 presents the regression results.

[11] We find from the exercise in the next section that, as compared with orders, cancellations have a much smaller effect on the CLV calculation. Therefore, our results on the driver value will remain qualitatively similar even if we assume cancellations do not impact future orders.

There is a strong and significant correlation between the waiting time and the number of drivers at work. Column (1) of Table 6 shows that a 1% increase in the number of drivers at work will reduce the time for a driver to accept the order by 0.31%, while column (2) shows that an increase in the number of drivers will further reduce the time for the driver to pick up by 0.32%. Although these results do not suggest a causal relationship, the positive correlations are consistent with the explanation of why more drivers at work lead to an increase in riders' orders and a decrease in cancellations.

Table 6. The Impact of Driver Supply on Cancellation

	(1)	(2)
	log (Accepting Time+1)	log (Picking Up Time+1)
log (Total Drivers+1)	-0.313**	-0.317***
	(0.156)	(0.116)
Week Fixed Effect	Yes	Yes
Day of Week Fixed Effect	Yes	Yes
Hour of Day Fixed Effect	Yes	Yes
Observations	3,040	3,040
R^2	0.020	0.019
Adjusted R^2	0.013	0.013

Notes: (1) the observation is at the order level; (2) *p<0.1; **p<0.05; ***p<0.01.

5 Value of Drivers for the Platform

One of the major goals of this study is to quantify the value of suppliers on sharing platforms. In our empirical context, a change in driver supply will have long-term impacts on the platform's business. Order cancellations indicate riders' dissatisfaction with the service. Prior literature (e.g., Magnini et al., 2007; Gelbrich, 2010; Cohen et al., 2021) suggests that such negative experiences may cause riders to reduce usage frequency and eventually switch to other platforms. More drivers at work help reduce cancellations, which in turn can affect future demand and profit.

To account for future impacts, one common approach in the CRM literature is to evaluate the CLV (e.g., Fader et al. 2005) of customers. Using this approach, we would calculate the discounted value of the profit flow each driver contributes to the platform. As we discussed in the Introduction, however, this calculation could be misleading, as drivers working at the same time could be substitutes for or complements of one another. Therefore, we take a different approach. Because the value of drivers to the platform comes from satisfying user needs and thus generating demand and revenue, we use the estimated cross-side network effect to measure the value. Instead of directly calculating the profit flow from each driver, we evaluate how the aggregate CLV of all individuals who register as platform users[12] is impacted by the change in driver supply. This approach helps address the above issue: if drivers are close substitutes, the change in driver supply will not have a significant impact on the aggregate CLV. However, if there is complementarity among drivers, an increase in the number of drivers at work can lead to demand expansion and thus an even larger increase in the CLV.

We measure the elasticity of the aggregate CLV with respect to the change in driver supply, i.e., the percentage change in CLV following a 1% change in the number of drivers at work. The source of the supply change can come from either new hires or extended work by existing drivers. We choose to measure elasticity because it is less sensitive to the difference in the size of the business.[13] Furthermore, many drivers work on a part-time basis for the platform, and the demand in the afternoon is very different from the demand at night. We thus study the impact of the change of drivers on the afternoon shift (i.e., from 12:00p.m. to 5:59p.m.) and the night shift (i.e., from 6:00p.m. to 11:59p.m.) separately.

[12] Note that a user may or may not be a rider on the platform, depending on their order decisions.

[13] Without measuring the elasticity, the impact of the change of one driver on our platform, for example, will be different from that on larger platforms, such as Uber or Lyft.

5.1 Calculating the CLV of a User on the Platform

We use the following equation to calculate the CLV of a representative user on the platform:

$$CLV = \frac{Number\ of\ Orders * (1 - Cancellation\ Rate)}{1 - Retention\ Rate} * Profit\ Per\ Order \quad (4)$$

where $Number\ of\ Orders * (1 - Cancellation\ Rate)$ represents the number of complete orders the user makes in a day, $Profit\ Per\ Order$ consists of the commission (i.e., 20% of the trip fare) that the platform takes from each complete order, plus the fixed fee that drivers pay, and $Retention\ Rate$ is the probability that the platform retains the user (i.e., continues to order in future). The right side of the equation therefore represents the expected total profit that a rider contributes to the platform in her lifetime, or the CLV.[14]

We have shown that the change in driver supply will directly affect $Number\ of\ Orders$ and $Cancellation\ Rate$. As cancellations reflect customer dissatisfaction with the service, a reduction in the cancellation rate will affect future orders as well as the retention rate. We hypothesize that a cancellation will cause the dissatisfied user to make orders less frequently in the future and thus increase the elapsed time, or the number of days before the next order. This will negatively affect the total number of orders. Further, it can increase the odds that the user never makes orders again, i.e., it will reduce the $Retention\ Rate$ in equation (4).

We use regressions to quantify the effects of cancellations. We use the experiment data to calculate the elapsed time (in days) following an order of all users and regress on whether the order was cancelled. We define churn as a binary variable that equals 1 if a user does not order again in the next half year after the last order in our data, and 0 otherwise.[15] We then run a linear probability model with churn as the dependent variable regressing on whether the order was cancelled. The regression results are reported in Table 7.[16]

[14] We assume the discounted rate to be zero because each period in the calculation is just a day. Results remain very similar if we impose a daily discount rate larger than zero.

[15] To run the regression we further obtain the usage data of all riders six months after the experiment.

[16] Since the elapsed time of the last order of a churned user cannot be defined, we do not include the last

Consistent with our hypotheses, following a cancellation, the user will have a longer elapsed time before the next order and is also more likely to churn.

Table 7. The Impact of Cancellations on Future Usage Behaviors

	DV: Elapsed Time	DV: Churn
	(1)	(2)
Cancellation	0.253***	0.089***
	(0.081)	(0.017)
Week Fixed Effect	Yes	Yes
Day of Week Fixed Effect	Yes	Yes
Hour Fixed Effect	Yes	Yes
Observations	3042	3411
R^2	0.564	0.123
Adjusted R^2	0.561	0.117

Notes: (1) the observation is at order level; (2) *p<0.1; **p<0.05; ***p<0.01.

With the estimates, we first calculate the aggregate CLV in the baseline scenario (i.e., without subsidy). We normalize the total number of users on the platform to 1. As most riders are not using the service on a daily basis, to calculate the number of orders in a day, we have to calculate the average elapsed time between orders. We use the following formula:

$$Average\ Elapsed\ Time = Elapsed\ Time_{complete} * (1 - cancellation\ rate) + Elapsed\ Time_{cancelled} * cancellation\ rate, \quad (5)$$

In the above equation, $Elapsed\ Time_{complete}$ and $Elapsed\ Time_{cancelled}$ are the predicted elapsed time following a completed and cancelled order, respectively. They are calculated from the regression results in column (1) of Table 7. The variable

orders in the first regression. As such, the number of observations in Column (1) is smaller than that in Column (2).

$cancellation\ rate$ is calculated using data from two months prior to the experiment, during which there were no subsidies offered to drivers.

Next, we use the normalized number of users (i.e., 1) to divide the elapsed time to calculate the average demand for rides in a day. We further calculate the proportions of orders in the afternoon and at night from data and multiply these proportions by the average daily demand to measure the average number of orders in the afternoon and at night. They are 0.150 and 0.048, respectively, suggesting that demand in the afternoon is about three times higher than that at night. Furthermore, we use the regression result in column (2) of Table 7 to calculate the baseline $Retention\ Rate$ in equation (4). Finally, we plug all of these numbers into the equation to obtain the aggregate CLV in the afternoon and at night of all users on the platform.[17]

When driver supply increases by 1%, the number of orders in both time slots will increase. We use the results from Column (2) of Table 5, which suggest that a 1% increase in driver supply will increase the number of orders by 2.007%, to calculate the changes. In addition, the cancellation rate will become lower, resulting in more complete orders. We use the results from Column (5) of Table 5, which indicate that a 1% increase in the number of drivers at work will reduce the cancellation rate by 0.48%, to calculate the new cancellation rate. The reduction in the cancellation rate will then reduce the elapsed time and churn rate. We use the results in Column (1) of Table 7 to calculate the new elapsed time and, with the increase in the number of orders in a day, calculate the new $Number\ of\ Orders$ in equation (4). We also use the new cancellation rate with the results in Column (2) of Table 7 to calculate the new $Retention\ Rate$. With all of these results, we obtain the new aggregate CLV with a 1% increase in the driver supply.

5.2 Results

Table 8 reports the percentage change (relative to the baseline scenario) in the daily number

[17] $Profit\ Per\ Order$ is calculated from data in the two months prior to the experiment when there is no subsidy.

of orders, the number of orders per driver, the retention rate, and the aggregate CLV, following a 1% increase in the number of drivers at work in the afternoon and at night, respectively. We find that the normalized total number of orders per day will increase by 2.077% in the afternoon and by 2.096% at night. The demand increase indicates that drivers are not perfect substitutes in both time slots; otherwise the demand changes should not be significant. The demand increase comes from two effects. The first is the direct effect, of which a higher supply attracts more orders. The second is the indirect effect, of which a higher supply will reduce cancellations and thus increase usage frequency. We also find that the average number of orders of each driver increases by 1.066% and 1.085% in the afternoon and at night, respectively. Such a surprising result indicates that, instead of causing demand cannibalization of orders from existing drivers, an increase in drivers actually expands the average demand of existing drivers; therefore, there is a complementary relationship between existing and new drivers.

In addition to the increase in orders, the retention rate will also increase by 0.005% in the afternoon and by 0.006% at night. The increases are small for two reasons: first, the effect of the increase in driver supply on the cancellation rate is quite small; second, the effect of a cancellation on the likelihood of churn is also small (see Column (2) of Table 7). Combining the above results, we show that the increase in driver supply has a major impact on demand but less on the retention rate.

The fourth row of Table 8 shows that, due to the complementarity relationship among drivers, the total (current and future) income of each driver will increase by 1.108% and 1.135% in the afternoon and at night, respectively. Finally, the last row of Table 8 shows that, following the 1% increase in drivers at work in the afternoon, the CLV of the platform will increase by 2.119% in that time slot. If the increase is at night, the CLV will increase by 2.146%. After we weigh the CLV by the relative demand of the two time slots, the CLV increase is 1.624% (0.501%) for a 1% increase in drivers in the afternoon (at night), relative to the total CLV (i.e., the sum of afternoon and night shifts) when there is no subsidy. This suggests that hiring more new drivers or incentivizing current drivers to work in the afternoon is more important for the platform than having more drivers working at night.

Table 8. Changes in CLV from 1% Increase in Driver Supply

Change in:	Afternoon	Night
Number of Orders	2.077%	2.096%
Number of Orders Per Driver	1.066%	1.085%
Retention Rate	0.005%	0.006%
Total Income Per Driver	1.108%	1.135%
CLV	2.119%	2.146%

5.3 Limitations

There are some limitations in our approach to calculate driver value, especially in the long run. First, we only consider the demand change under a 1% change in driver supply. In the long run, however, the increase in the driver supply may lead to more competition among drivers and thus to driver exits. In this case, CLV changes will be overestimated. We find that, however, the income of each driver will increase instead, suggesting that drivers are in a complementary relationship with one another. As such, the platform should be able to attract more drivers in future and further increase the aggregate CLV. Therefore, it is more likely that the CLV changes in Table 8 are underestimated.

On two-sided platforms, cross-side network effects could be bilateral. That is, the increase in demand can also lead to an increase in supply. Since our calculation of driver value is only based on the effect of supply on demand, the potential impact of the increased demand on future driver supply has not been taken into account. In this sense, the CLV changes we have shown are just a partial equilibrium outcome that is likely to be underestimated when the full equilibrium outcome is realized.

Finally, we caution the reader that the CLV calculations are based on the current levels of demand and supply on the platform; the results could be different for another platform with a different balance of demand and supply. For example, if there are already too many drivers relative to the number of riders in a time slot, further increasing the number of drivers may only take away orders from current drivers and will not increase the aggregate CLV for the platform.

5.4 Optimizing the Subsidy Scheme

Understanding the value of drivers can have important substantive implications for sharing platforms. As an example, suppose the ride-sharing platform is losing drivers after the pandemic, as Lyft did. In this case, it can use the CLV results to evaluate the monetary impact on the business. It can also investigate the costs and benefits of offering monetary incentives to motivate existing drivers to work longer hours. In this subsection, we will use data from the experiment to illustrate how the car-sharing platform can evaluate such tradeoffs and use the results to optimize the subsidy schedule.

We first run a counterfactual in which the platform offers different levels of subsidies to all drivers in one week based on our findings. The subsidies range from $1 to $6 per complete trip. We calculate the predicted number of drivers at work under different subsidies, using the first-stage regression results in Column (1) of Table 4. We then follow the same procedure described in the previous subsections to calculate the net value, i.e., the corresponding aggregate CLV subtracted by the cost of subsidies, of the platform, and compare them with the net value when there is no subsidy. The results suggest that when the platform offers a $1 subsidy for every trip for all drivers, the net value will drop by 9.413%. A larger subsidy will further reduce the value: When the platform offers the maximum $6 subsidy, the net value will drop by 97.954%. This is because the average revenue the platform obtains from each trip is already low. The subsidy is therefore a significant cost for the platform that cannot be compensated by the CLV gains following the increase in driver supply.

Given the above results, we ask whether the platform can gain from offering heterogeneous subsidy schemes to different types of drivers. Since many drivers work on a part-time basis, we speculate that they do not respond to the offered subsidies in the same way across time slots. Table 2 indicates that the work preferences of active and inactive drivers differ in the afternoon and at night, as well as on weekdays and weekends. To investigate the potential heterogeneity in the response to subsidies, we repeat the first-stage regressions for the two types of drivers separately. We also interact the log (Subsidy+1) with the afternoon, night, weekday, and weekend indicators in the regressions. Doing so helps us understand how different types of drivers react to subsidies in different time slots.

The results shown in Table 9 reveal that active drivers have a high elasticity in both weekday and weekend afternoons. This is consistent with the observation that active drivers prefer to work in the afternoon. An afternoon subsidy therefore can be more effective at incentivizing drivers to work. In comparison, active drivers have either negative or insignificant elasticity at night,[18] suggesting that offering subsidies at night is not effective. In contrast, inactive drivers only significantly respond to subsidies on weekday nights. Interestingly, Table 2 shows that they also have low work hours on weekday nights. We speculate that this is because, unlike active drivers, inactive drivers are primarily part-time workers for the platform. Their availability depends on the time schedule of the main job, which is likely to be during the daytime. As such, there is more room to increase their work hours during weekday nights.

[18] It is unclear for us why the coefficient for log (Subsidy+1) * Weekday Night is negative; however, the coefficient is small in magnitude and only marginally significant.

Table 9. The Impact of Subsidy on Driver Type and Time Slots

	DV: log (Total Drivers+1)	
	(1) Active	(2) Inactive
log (Subsidy+1) * Weekday Afternoon	0.149***	0.149
	(0.044)	(0.117)
log (Subsidy+1) * Weekday Night	-0.041*	0.124**
	(0.021)	(0.056)
log (Subsidy+1) * Weekend Afternoon	0.144***	-0.143
	(0.044)	(0.119)
log (Subsidy+1) * Weekend Night	0.030	0.045
	(0.026)	(0.069)
Week Fixed Effect	Yes	Yes
Day of Week Fixed Effect	Yes	Yes
Hour of Day Fixed Effect	Yes	Yes
Observations	276	276
R^2	0.635	0.416
Adjusted R^2	0.600	0.360

Notes: (1) the observation is at the hour level; (2) *p<0.1; **p<0.05; ***p<0.01

The above results suggest that subsidies can be more effective if the subsidy targets different types of drivers in different time slots. Therefore, we run counterfactuals by offering subsidies to active and inactive drivers in (1) weekday afternoons, (2) weekday nights, (3) weekend afternoons, and (4) weekend nights. The results are reported in Table 10. We find that, for active drivers, it is profitable for the platform to offer subsidies at the value of \$1 or \$2 in the afternoon during weekdays and weekends, as the changes of the net value are positive. The optimal subsidy level is \$1. For inactive drivers, in contrast, it is only profitable for the platform to offer subsidies on weekday nights, and the optimal level of subsidy is $2.

Table 10. Changes in the Net Value under Different Subsidy Schemes

	Weekday				Weekend			
	Afternoon		Night		Afternoon		Night	
Subsidy	Active	Inactive	Active	Inactive	Active	Inactive	Active	Inactive
1	5.644%	-0.634%	-3.959%	0.470%	2.917%	-0.356%	-2.289%	-0.229%
2	3.975%	-1.267%	-7.028%	0.597%	1.861%	-0.712%	-4.579%	-0.459%
3	-1.877%	-1.901%	-9.714%	0.564%	-1.450%	-1.067%	-6.868%	-0.688%
4	-10.667%	-2.535%	-12.180%	0.431%	-6.337%	-1.423%	-9.157%	-0.917%
5	-21.732%	-3.169%	-14.498%	0.230%	-12.439%	-1.779%	-11.446%	-1.147%
6	-34.663%	-3.802%	-16.710%	-0.023%	-19.533%	-2.135%	-13.736%	-1.376%

In practice, if the two types of drivers are targeted with different incentives, the platform has to make sure that the subsidy scheme is not perceived as unfair. Otherwise, some drivers could become upset, which would have negative unintended consequences. Therefore, we consider offering the same amount of subsidy to both types of drivers. However, active drivers will receive the subsidy in the afternoon, while inactive drivers only get the subsidy at night. Because the amount of subsidy is the same, and the afternoon and night shifts both last six hours, such a subsidy scheme is fair to everyone. In addition, the fact that inactive drivers are only responsive to subsidies offered at night indicates that they are better off than subsidies offered in the afternoon.

Based on results in Table 9, we observe that active drivers' supply responds positively to subsidies for both weekday and weekend afternoons, whereas inactive drivers' supply responds positively only to weekday nights. Therefore, there are two possible subsidy designs that can deliver more desirable gains for the platform, namely subsidizing active drivers in afternoons and inactive drivers at night (1) only for weekdays and (2) for both weekdays and weekends. We consider the second design because it is possible that the net value gains from active drivers during the weekend afternoons may exceed the loss from inactive drivers. In terms of subsidy levels, based on the results shown in Table 10, we find that a \$1 subsidy is better for active drivers for both weekday and weekend afternoons. However, for inactive drivers, while \$1 is better on weekend nights, \$2 is better on weekday nights. Thus, we evaluate the subsidy levels at both \$1 and \$2. In short, we test four different scenarios with varying subsidy timeslots and levels.

We find that, among these four scenarios, the optimal subsidy scheme is, for both weekdays and weekends, offering a \$1 subsidy to active drivers in afternoons and a \$1 subsidy to inactive drivers at nights. The platform's net value will increase by 8.801%. The results suggest that the number of orders and the total revenue per driver will also increase by 5.652% and 21.513%, respectively, under such a subsidy scheme. As a result, we demonstrate that optimizing the subsidy can not only enhance the platform's business performance but also benefit drivers due to their complementary relationship.

6 Conclusion

Cross-side network effects are ubiquitous on two-sided platforms and have important impacts for these platforms' business growth and long-term profitability. In this paper, we study the cross-side effect of driver supply on the order requests and cancellations of riders on a ride-sharing platform using a field experiment. We tackle identification challenges by exogenously manipulating subsidies per trip offered to drivers in the experimental design and use them as the instrumental variable for driver supply. We illustrate how the design ensures the manipulated subsidies are a valid instrument and how other concerns, including the exclusion restriction, the naturalness of the manipulation, and the external validity of the findings should be considered in the experimental design.

We find that the increase in the driver supply significantly encourages riders to make order requests and prevents order cancellations. The results indicate a large, positive cross-side network effect from the driver side to the rider side. Using these results, we quantify the long-term impact of driver supply on the aggregate CLV of users on the platform. We find that increasing new hires of drivers or incentivizing drivers to work longer during the afternoon shift will strongly increase the total CLV of riders.

Our findings offer important managerial implications for platform managers. The large demand elasticity with respect to the change in driver supply in our results indicates how platforms may increase demand and revenue by incentivizing a higher driver supply. Further, our experiment demonstrates that increasing driver supply can help the platform prevent excessive cancellations and improve the user experience, with long-lasting impacts on the business. The CLV change can be used as an important performance metric for platforms when evaluating the returns of subsidizing drivers.

We have discussed several limitations in our CLV calculations. Future research should investigate the impact of increasing driver supply on the entry and exit of drivers. The bilateral nature of the cross-side network effects should also be studied. In addition, we made some shortcuts in the CLV calculation. For example, we did not pin down the causal effects of cancellation on the next order time and churn. Furthermore, non-linear monetary incentives (e.g., quota or increasing subsidization) could be a more efficient way to encourage drivers to work more, and these have not been studied in this paper. Finally, while we focus on order requests and cancellations on the demand side, other outcomes, such as driver ratings and tips, may also be important to the platform. We believe future research can provide further insights to address all of these issues.

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