Demand and Consumer Surplus in the On-demand Economy: the Case of Ride Sharing *

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Abstract

How is economic value created by on-demand ride-sharing platforms? We exploit granular data on dynamic pricing and wait time on Uber and Lyft at type-route-time level, and public data on taxi and public transit in New York City. We estimate a discrete-choice demand model that allows substitution among transportation modes. Counterfactual analyses show three main findings. First, platform users gain 72 cents per dollar spent on these platforms. Second, welfare gains are disproportionately higher in locations and times that have been underserved by taxis and public transit. Third, we estimate that 64% of welfare gains come from dynamic pricing used by these platforms.

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1 Introduction

The rise of the on-demand economy marks one of the leading changes in the digital age. Ride-sharing platforms, such as Uber and Lyft, differ from traditional taxis in key aspects, such as real-time smartphone app-based matching, dynamic pricing that balances real-time supply and demand, and flexible driver work arrangements. This paper empirically studies one fundamental question: how is economic value created by these ride-sharing platforms? Answering this question will help managers and policy makers understand the sources of welfare changes from ride-sharing platforms, which is the first step towards optimizing user experience on the platform and public policy making.

There are two central challenges in identifying welfare sources. First, different transportation modes are substitutes. This implies that researchers will overestimate the gains from ride-sharing platforms if they do not model riders' substitution towards other transportation options in the absence of these platforms. Second, researchers typically lack detailed data to adequately control for heterogeneities across different routes at different times. These data are essential because demand is route-specific and time-sensitive in this setting.

In this paper, we conduct a demand estimation that directly addresses the first challenge by allowing substitution among alternative transportation modes at the route-time level. Specifically, the consumer's problem is a discrete choice among ride-sharing services, taxis, and public transit, where the utility of each choice depends on its price, wait time, as well as other observed and unobserved characteristics. The real-time market shares, however, are simply not available, because ridership data of public transit, the "outside" option in our model, does not exist at the route-time level.[1] Therefore, existing discrete-choice demand estimation methodologies such as those in Berry et al. [1995] and Ghose and Han [2014] do not apply in this setting. Instead, we establish our identification by leveraging the relative shares of the "inside" options.

To address the second challenge, the lack of granular data, we exploit Uber and Lyft application programming interfaces (API hereafter) query data on dynamic pricing and wait time, at granular type-route-time levels of New York City (NYC hereafter). We augment these data with the population of taxi trip records and Uber/Lyft pick-up information published by NYC Taxi and Limousine Commission (TLC hereafter). Due to the lack of information on drop-off with TLC Uber and Lyft trips, we collected field data on 75,704 trip records from 443 Uber and Lyft drivers.

[1] This is due to the technical feature of the subway system that does not require passengers to swipe their card at the destination station. Therefore, the system does not record ridership data at the route level.

The data present interesting model-free evidence on the welfare impacts of ride-sharing platforms: first, Uber and Lyft make ride services conveniently available in many locations in NYC, while taxis are heavily concentrated in Manhattan; second, dynamic pricing seems to effectively balance supply and demand, where high prices lead to shorter subsequent wait times and more subsequent pick-ups.

Our estimation, like other demand estimation studies, is subject to price endogeneity, given that Uber and Lyft pricing algorithms can potentially take into account factors that affect demand but are unobserved to the researchers. Wait time is also endogenous because it is the matching outcome of riders and drivers, which is likely correlated with unobserved demand shocks. We use instrumental variable strategies to causally identify the model by exploiting a unique design feature of ride-sharing platforms. Specifically, our instrument for the prices at a focal location is the average price across the origins of all trips arriving at the focal location. The rationale is that Uber and Lyft applications do not require information on destinations before committing to a price.[2] This suggests that origin prices are not likely affected by destination demand shocks and therefore this satisfies the exclusion restriction assumption in the IV regressions. On the other hand, this instrument is correlated with the endogenous price variable, because origin prices affect the number of cars arriving at the focal location, which directly affects the supply at that location. Following a similar logic, we instrument on the wait time with the number of drop-offs in all neighboring areas.

The demand parameter estimates are sensible: price-sensitive consumers value time and dislike waiting, with sensible heterogeneity across locations and time. For example, high wait time sensitivity and low price sensitivity are found on riders in Lower Manhattan during evening rush hours on weekdays, which may be driven by the preference of financial industry practitioners. Consumers going to the airport have similar sensitivities. In addition, consumers value service characteristics including luxury and capacity, which are made conveniently available on ride-sharing platforms compared to conventional transportation modes.

We estimate consumer welfare impacts of Uber and Lyft in the sense of compensating variation — the dollar amount that consumers need to be compensated with in the absence of Uber and Lyft so that they maintain the same level of utility as before. This calculation then requires estimating the equilibrium wait time of taxis in the absence of Uber and Lyft and then simulating consumers' optimal choices accordingly. A simple model with taxi capacity constraint predicts that

[2] This old version of Uber was updated to upfront pricing after our sample period, and now riders need to input destinations to get a fixed price. Lyft also went through a similar design change.

the average taxi wait time increases when ride-sharing platforms are removed from the market, due to the substitution effect that leads to a greater taxi ridership.

A comparison between consumers' utility when ride-sharing platforms are present and their counterfactual utility when these platforms are absent leads to an estimate of the welfare gain of 72 cents for each dollar spent on these platforms. This welfare gain is further attributed to different welfare channels, namely accessibility, price, luxury, capacity, and comfort, where we find that more than half of the consumer surplus comes from the better accessibility (short wait time) of Uber and Lyft. More interestingly, the per-dollar consumer surplus is greater in the outer boroughs than in Manhattan, and during rush hours than during non-rush hours. These locations and times have been underserved by taxis and public transit, and the entry of ride-sharing platforms has greatly benefited consumers in these areas. Furthermore, we find that taxi riders gain 16 cents per dollar spent, because taxi wait time becomes shorter as a result of some consumers switching to ride-sharing platforms.

To the extent that the essential difference between traditional taxis and ride-sharing platforms is the real-time app-based matching technology combined with dynamic pricing, keeping one and removing the other will help disentangle the relative contributions of the two mechanisms. We construct a counterfactual where taxis adopt the same app-based matching, and we find a consumer welfare gain due to the entry of Uber and Lyft as large as 64 percent of the welfare estimate in the benchmark counterfactual. This finding sheds light on the value added of dynamic pricing, which appears to make real-time matching of riders and drivers more efficient than having a fixed taxi fare. Although the information system itself generates extensive values (Bhargava and Choudhary [2004]), our results suggest that the complementarity (Aral et al. [2012], Bresnahan et al. [2002], Tambe et al. [2012]) between the technology and the pricing scheme likely has contributed to the success of ride-sharing platforms.

To our knowledge, this paper is the first consumer welfare analysis of ride-sharing platforms that accounts for substitution among transportation modes. The most closely related work to ours is Cohen et al. [2016], who estimate the consumer welfare of UberX at $1.6 per dollar spent. Our work differs from theirs in two aspects: first, allowing for consumer substitution among alternatives leads to less biased price sensitivity estimates[3]; second, we are able to disentangle the distinct welfare sources, which are necessary in understanding how consumers make purchase decisions and

[3]More precisely, we allow for competition and substitution at the route level, which we believe is a more realistic unit (compared to an aggregation of routes) to study consumer purchase decisions in the market of rides.

consequently how platforms can better design their strategies.

This study adds to the strand of literature on how digital platforms create efficiency gains by providing convenience and reducing transaction costs of platform sides (Bakos [1997], Bakos [1998], Brynjolfsson and Smith [2000], Brynjolfsson et al. [2003], Brynjolfsson et al. [2011], Davis [1989], DeLone and McLean [1992], Parker and Van Alstyne [2005]). Particularly, this paper provides direct empirical evidence on how centralized information systems improve the matching of the platform's two sides, compared to the decentralized taxi system (Einav et al. [2016], Fradkin [2017]). To the extent that matching frictions are equilibrium outcomes of the taxi market (Lagos [2000], Lagos [2003]), Cramer and Krueger [2016] show the efficiency gain of ride-sharing platforms evidenced by higher utilization rate than taxis. Buchholz [2015] and Frechette et al. [2016] simulate substantial welfare gains from the use of matching technologies that resemble ride-sharing platforms, which is also in accordance with our welfare estimates. Given that price adjustments on the platforms require minimal costs (Brynjolfsson and Smith [2000]), this paper further supports dynamic pricing as a feasible and efficient way to balance supply and demand, as argued in Hall et al. [2015] and Castillo et al. [2017].

Using a discrete choice framework, this paper projects the product or service into the characteristic space and identifies the distinct welfare channels, which is in the basic spirit of demand estimation studies such as Goolsbee and Petrin [2004], Nevo [2000, 2001], Petrin [2002]. The welfare gains from richer product assortments on the platforms are also consistent with the "love-of-variety" story as in Brynjolfsson et al. [2003] and Quan and Williams [2016]. As a contribution to the literature, we are among the first to extend the discrete choice demand estimation into the real-time setting with an application of the on-demand economy.

Our research also joins a growing literature that studies the sharing economy, such as work flexibility (Chen et al. [2017], Hall and Krueger [2016], Hall et al. [2017]), drunk driving (Greenwood and Wattal [2017]), entrepreneurial activity (Burtch et al. [2016]), local consumption patterns (Zhang and Li [2017]), sexual harassment (Park et al. [2017]), car ownership (Gong et al. [2017]), traffic congestion (Li et al. [2016]), as well as demand and welfare studies of Airbnb (Farronato and Fradkin [2017], Zervas et al. [2014], Zhang et al. [2017]).

The remainder of the paper is structured as follows. Section 2 gives an overview of the industry and the market of rides. Section 3 provides a detailed description of the data. Section 4 describes the demand estimation and identification procedure. Section 5 discusses the estimation results. Section 6 presents a model of taxi market equilibrium. Section 7 illustrates the welfare calculation by studying two counterfactuals. Finally, Section 8 concludes this paper.

2 Market for Rides in NYC

Household car ownership in NYC is among the lowest across cities in the U.S., with more than half of NYC households vehicle-free.[4] Residents of NYC, as well as visitors, rely heavily on public transportation to get around the city. The NYC subway system is one of the largest and busiest subway networks in the world, with an annual ridership of more than 638 million rides in 2016.[5] Another big component of the NYC public transportation system is the bus network, whose ridership exceeded 125 million in 2016.[6] So, public transportation plays an important role in New Yorkers' daily life.

An alternative way of traveling is by taxi cabs. NYC has one of the largest and most extensively operated taxi systems in the country. Yellow medallion taxis, serving the city for over a century, have become one of the cultural staples of NYC. TLC has strict control over the number of medallions in the market, and there were 13,587 yellow medallion licenses in 2015. Taxi fare changes are infrequent.[7] While yellow medallion taxis can pick up street hails in all five boroughs of NYC, pick-ups are heavily concentrated in Manhattan (Figure 3). As an effort to increase taxi coverage in neighborhoods outside Manhattan, in August 2013, TLC introduced street hail livery cabs, commonly known as green boro taxis, which have limited pick-up areas. [8] By the end of 2015, 7,676 green boro taxi licenses were active in the market.

With the wide adoption of smartphones, application-based ride-sharing platforms were designed by companies to enable ride requests via apps. Uber entered the NYC market in May 2011 and has become the largest player in the market. Lyft, Uber's largest competitor, entered the NYC market in July 2014. Besides Uber and Lyft, there are also a few other ride-sharing platforms that are relatively small in market shares, such as Via, Gett, and Juno. These platforms share real-time supply conditions with the riders and practice dynamic pricing to allow for real-time adjustment of demand and supply. For example, Uber's interface (Figure 1) shows the rider the estimated wait time at the pick-up location and requires the rider to accept a certain dynamic price multiple

[4] http://ns.umich.edu/new/releases/21923-hitchin-a-ride-fewer-americans-have-their-own-vehicle

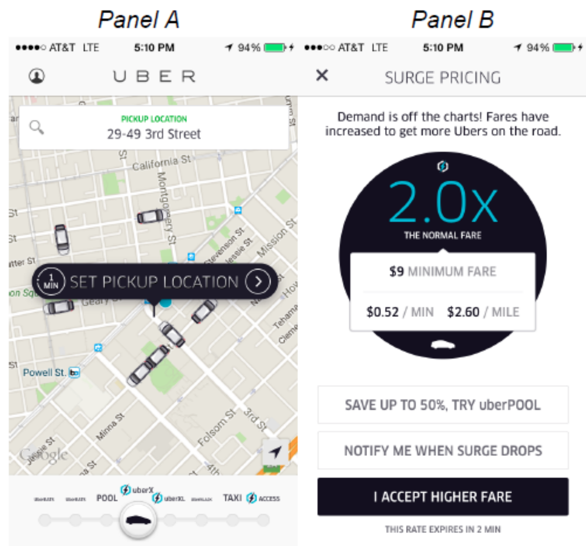
[5] http://web.mta.info/nyct/facts/ridership/ridership_bus_annual.htm

[6] http://web.mta.info/nyct/facts/ridership/ridership_busMTA_annual.htm

[7] Taxi fare has been increased only once in the past decade, in September 2012.

[8] Green boro taxis share the same price structure as yellow medallion taxis; they can accept street hails anywhere in NYC except south of West 110th Street and East 96th Street in Manhattan and the airports in Queens (although they can take pre-arranged trips in these airports) and they may drop passengers off anywhere. For details, see http://www.nyc.gov/html/tlc/html/passenger/shl_passenger.shtml

Figure 1: Uber Application Interface (source: Cohen et al. [2016])



before requesting a trip. Drivers join the platforms as independent contractors, drive their own cars, and have flexibility in work location, schedule, and intensity. The prices riders pay are set by the platforms and often changed frequently in response to changing market conditions. The revenues drivers get are usually the prices riders pay, net of a fixed rate of commission charged by the platforms. In addition, these platforms provide differentiated service types. For example, UberX is the regular ride service with non-luxury sedans, while UberBlack is the luxury black car service. Payments are handled by the application, which facilitates transactions. Similar to other platforms in the digital economy, ride-sharing platforms allow riders and drivers to rate the transactions. Over the past few years, ride-sharing platforms have experienced rapid growth in both driver and rider adoptions.

The entry of tech-aided ride-sharing platforms dramatically changed the landscape of the market for rides. A direct impact is on the taxi system, where ridership has dwindled constantly in the past few years. The number of yellow medallion trips daily fell from 463,701 in November 2010 to 336,737 six years later, and the total daily revenue fell from $5.17 million to $4.98 million.[9] Once over a million dollars, the average auction price of a medallion license has dropped significantly as well.[10] The rise of ride-sharing platforms may also have contributed to the fall in subway ridership.[11]

[9] https://www.nytimes.com/2017/01/15/nyregion/yellow-cab-long-a-fixture-of-city-life-is-for-many\discretionary{-}{}{}a-thing-of-the-past.html?hp&action=click&pgtype=Homepage&clickSource=story-heading&module=second-column-region&region=top-news&WT.nav=top-news&_r=0

[10] http://www.nyc.gov/html/tlc/html/archive/archive_med_transfer_2016.shtml

[11] https://www.nytimes.com/2017/02/23/nyregion/new-york-city-subway-ridership.html

3 Data and Model-free Evidence

3.1 Data Summary

Our data set focuses on NYC, which consists of five boroughs, namely the Bronx, Brooklyn, Manhattan, Staten Island, and Queens. The city is further divided by TLC into 263 taxi zones, 69 of them being in Manhattan. These zones vary in size, and normally Manhattan zones are smaller than zones in the outer boroughs.[12] The typical Manhattan taxi zone is six by six street blocks wide. Throughout this paper, we treat these taxi zones as our basic geographical units of analysis.

First, we collected information on dynamic pricing[13], wait time, trip duration estimates, and trip distance estimates using the Uber and Lyft API. The dynamic pricing and wait time were queried at approximately 1-minute intervals for all 263 pick-up zones. For each of the 263 by 263 routes, we estimated trip distance, trip duration, and trip cost approximately once every 4 hours.[14] All of the above-mentioned data were collected for all service types available on both platforms, namely UberX, UberXL, UberBlack, UberSUV, UberPOOL, Lyft, LyftLine, and LyftPlus [15]. Summary statistics are shown in Table 5. One striking feature of the data is how quickly prices and wait time change across space and time (Figure 2). In addition, we queried the same set of information on UberTaxi, which was a function on the Uber platform that riders could use to request taxi cab rides. Unlike other service types on Uber, the fare was still metered like a regular taxi ride and Uber charged a small booking fee.[16]

Second, we obtained the population of taxi trip records from NYC TLC. These records, summarized in Table 6, contain detailed trip information, such as pick-up and drop-off date and time, the GPS coordinates of the pick-up and drop-off locations, number of passengers, trip fares, etc. TLC also publishes FHV trip records, where we identified Uber and Lyft trips by the dispatching base numbers.[17] Far from the level of detail of taxi trip records, Uber and Lyft trip data only contain

[12] Refer to the following link for a shape file of taxi zones provided by TLC: http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml.

[13] Dynamic pricing is called "surge pricing" on Uber and "prime-time" pricing on Lyft. For simplicity, we use "surge" to refer to the practice of dynamic pricing on both platforms throughout the text. For example, "surge multiple" refers to the multiples of the base price on both platforms.

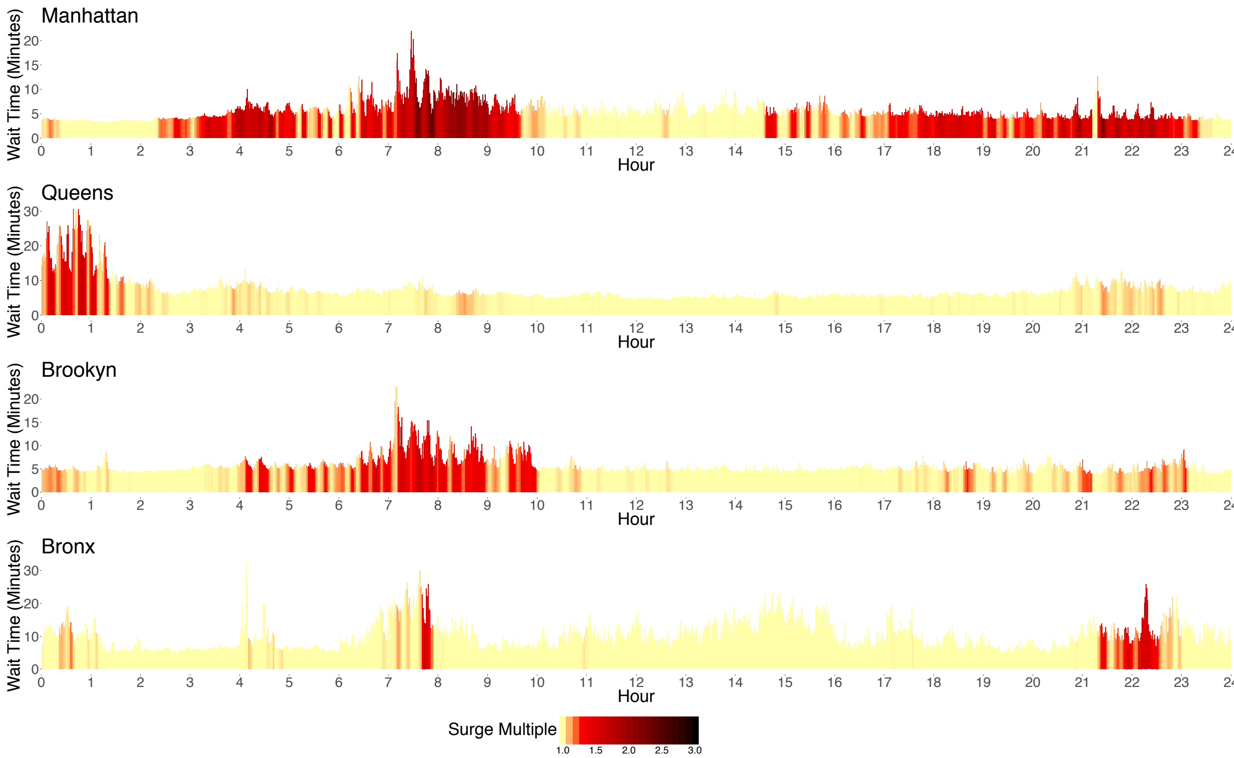
[14] Refer to the data appendix A.1 for more details.

[15] UberX and Lyft are the regular and mostly used service types on each platform, respectively. UberXL and LyftPlus are service types with cars of larger capacity, which usually seat up to 6 passengers. UberBlack and UberSUV are the luxury options on Uber platform. UberPool and LyftLine are the carpool options on Uber and Lyft, respectively.

[16] UberTaxi was first introduced in NYC in September 2012 and quickly pulled back in October 2012. It returned to NYC in April 2013 and operated till September 2016. Uber does not handle the payment with UberTaxi. For each requested trip, Uber charges a $2 commission fee.

[17] Refer to http://www.nyc.gov/html/tlc/downloads/pdf/find_a_ride.pdf. See the data appendix A.2 for how

Figure 2: Surge Multiple and Wait Time Change Rapidly across Space and Time (UberX, Monday, June 6, 2016)



Note: This graph plots how UberX minute-level surge multiple and wait time, averaged over all zones of a given NYC borough, vary across time of the day, on Monday, June 6th 2016. Surge multiples are in varying shades as illustrated by the legend, and wait time are measured by the bar length.

pick-up date, time, and locations in the form of taxi zones. Restricted by this, we then mapped the GPS coordinates of taxi trips into their corresponding taxi zones so that taxi and ride-sharing trips are in the same geographical unit.

Uber and Lyft trip records provided by TLC lack information on drop-off locations, drop-off time, and service types. This data limitation hinders analysis at the type-route-time level. To address this problem, we conducted field data collection to acquire approximately 75,704 historical trip records from 443 Uber and Lyft drivers in NYC. We discuss the sampling methods and randomness of the data in the appendix (A.3). This data set contains detailed information about the trips, such as pick-up location and time, drop-off location and time, price and surge multiple, wait time, service type, trip distance, and trip duration (summary provided in Table 7). We further include the total travel time via subway for all the 263×263 routes, which we queried from Google Maps API.

the base numbers are identified.

Each of these data sources cover different time periods. We used the overlapping period between June 1, 2016 and August 31, 2016 as our analysis sample.

3.2 Model-free Evidence

3.2.1 Uber and Lyft Location-time Coverage

The data present some interesting model-free evidence on consumer welfare gains of the ride-sharing platforms. First of all, the sheer volume of realized transactions on Uber and Lyft indicates consumers' valuation, by revealed preference. As Figure 3 demonstrates, while taxi pick-ups are concentrated in Manhattan Core, shares of Uber and Lyft pick-ups are significantly higher in the outer boroughs. To the extent that it is much more difficult to hail a cab in the outer boroughs than in Manhattan, Figure 3 suggests a disproportionate welfare gain due to the availability of ride-sharing services in neighborhoods that are traditionally underserved by taxis.

Figure 3: Ride-sharing Platforms Cater to the Outer Boroughs More than Manhattan

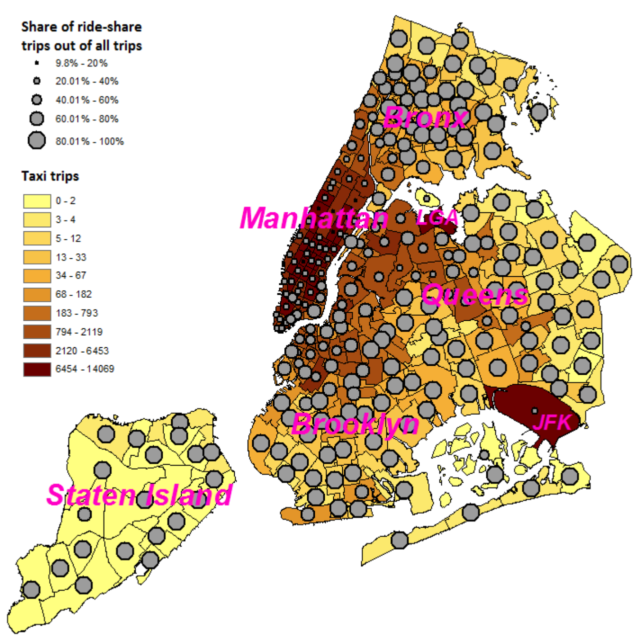
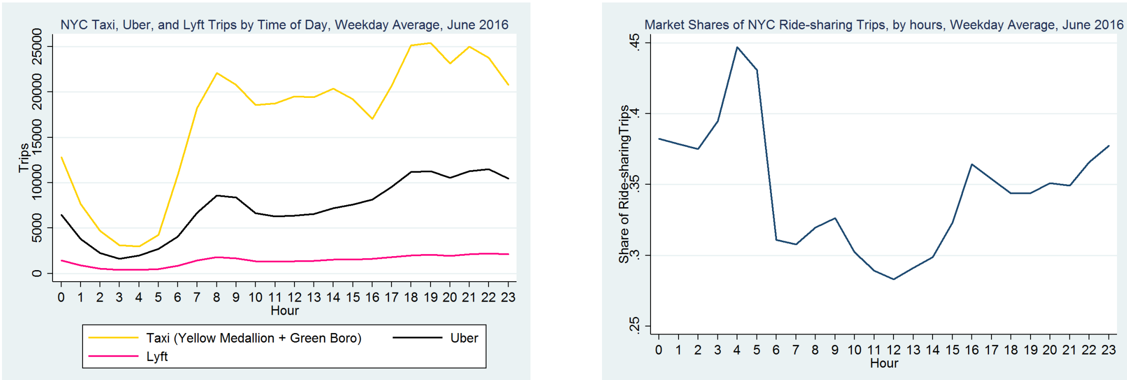


Figure 4 shows how taxi and ride-sharing pick-ups covary across hours of the day. Overall, taxi and ride-sharing trips follow the same trend, except around 4 a.m. and 4 p.m., when ride-sharing platforms gain larger shares. This is likely due to the early morning and afternoon taxi shift

Figure 4: More Ride-sharing Trips during Taxi Shift-change Hours



(a) NYC taxi, Uber, and Lyft trips by time of an average weekday

(b) Shares of Uber and Lyft trips by time of an average weekday

Table 1: Pick-up Coverage of Taxi, Uber, and Lyft

Level	**Taxi**	**Uber**	**Lyft**	**Uber+Lyft**	**Maximum**
pickupzone	98%	99%	99%	99%	100%
pickupzone-day	89%	98%	97%	98%	100%
pickupzone-day-hour	64%	89%	76%	90%	100%
pickupzone-day-hour-15min	50%	74%	52%	78%	100%

Note: Each of the numbers shown in the table represents the percentage of all unique location-time cells with at least one pick-up requested (June 2016 only). For example, the total number of cells at the finest level ("pickupzone-day-hour-15min") is 757,440 (263 x 30 days x 24 hours per day x four 15-minute intervals per hour). The number 50% for taxi, for example, means that taxi trips are observed in 50% of 757,400 cells.

changes[18], which create an out flux of taxi cabs, mostly from Manhattan to the outer boroughs [19]. These patterns are indicative of consumers' substitution toward ride-sharing services during the hours when taxis are less available.

Table 1 further compares the pick-up coverage of taxis, Uber, and Lyft across both space and time. The numbers in the table represent the share of all space-time combinations, at each space-time level, where at least one pick-up took place. The numbers demonstrate that both Uber and Lyft exceed taxis in coverage, on every level. In addition, these differences in coverage are larger on finer space-time levels.

Table 2: Dynamic Pricing is Difficult to Predict

	X	XL	SUV	Black	Pool	Lyft	Line	Plus
Fixed Effects				**Surge Multiple**				
pickupzone	0.08	0.08	0.01	0.02	0.07	0.05	0.05	0.05
pickupzone-hour	0.16	0.15	0.03	0.03	0.13	0.11	0.11	0.11
pickupzone-hour-weekend	0.21	0.20	0.05	0.05	0.18	0.13	0.13	0.13
pickupzone-hour-weekday	0.24	0.23	0.07	0.07	0.21	0.17	0.17	0.17
pickupzone-hour-weekday-15min	0.27	0.26	0.10	0.10	0.24	0.19	0.19	0.19
Fixed Effects				**Surge Dummy**				
pickupzone	0.12	0.12	0.07	0.07	0.11	0.07	0.07	0.07
pickupzone-hour	0.17	0.16	0.07	0.07	0.16	0.11	0.11	0.11
pickupzone-hour-weekend	0.20	0.19	0.08	0.08	0.20	0.14	0.14	0.14
pickupzone-hour-weekday	0.22	0.22	0.09	0.09	0.22	0.17	0.17	0.17
pickupzone-hour-weekday-15min	0.24	0.24	0.10	0.10	0.24	0.18	0.18	0.18

Note: Each of the numbers shown in the table represents the R-squared of the regression of the surge multiple (or surge dummy in the lower panel) on a set of location-time fixed effects. "Weekend" is a dummy for weekend; "Weekday" is a set of dummies for 7 days of the week; "15min" is a set of dummies for the four 15-minute periods of an hour, specifically 0 - 14, 15 - 29, 30 - 44, 45 - 59. Each level of the fixed effects is a cross-product of the respective dummies.

3.2.2 Dynamic Pricing

Efficiency can be gained when dynamic pricing effectively balances supply and demand (Hall et al. [2015]) [20]. One should expect a more important role of dynamic pricing when the market conditions are stochastic. When demand is high relative to supply, a higher price than normal commanded by a pricing algorithm likely reduces demand and incentivizes supply. As a result, more trips are requested in equilibrium and, consequently, the welfare increases. Consistencies with this intuition are found in the data, as detailed next.

First, dynamic pricing is highly volatile and difficult to predict, reflecting the randomness of the underlying market conditions that require frequent price adjustments. In the upper panel of Table 2, we report the R-squared of the regression of the surge price, at pickupzone-minute level, on the corresponding set of location-time fixed effects, for a given service type. These numbers measure how well one can predict the dynamic prices using the location-time fixed effects. Across service types, the R-squared increases as more layers of fixed effects are controlled for. However, the increase in the R-squared is rather small; even at a level as fine as pickupzone-hour-weekday-15min,

[18] The majority of yellow medallion cabs are operated two shifts per day.

[19] Most of taxi leasing garages are located outside of Manhattan.

[20] Guda and Subramanian [2017] propose an alternative theory on the strategic role of dynamic pricing.

only a maximum of 27% of variations in surge multiples can be explained. The situation barely changes, as shown in the lower panel, when the same set of regressions are conducted on the surge dummy (1 when surge multiple is above 1.0, 0 otherwise).

We then examined how dynamic pricing predicts subsequent wait time and pick-ups. In Table 3, each cell represents a regression of the first difference of wait time on the surge multiple, for a given service type and at a given minute of the next 5-minute period. The numbers shown in the table are the associated regression coefficients (in the unit of seconds of time), all of which are negative and significantly estimated at the 1% level. These numbers indicate that a high surge multiple predicts a decrease in subsequent wait time, and this decrease is present for at least 5 minutes following the surge. In Table 4, we regress subsequent pick-ups on dynamic prices, where the positive coefficients estimates of own-price-own-trip regressions (numbers in italics) suggest that a high surge price leads to more trips requested. For example, an increase of Uber surge multiple by 1 (i.e., doubling the price) predicts 0.88 more trips requested in the next 5 minutes, and 1.80 and 2.79 in the next 10 and 15 minutes, respectively. The numbers with Lyft (0.00, 0.06, and 0.13) are substantially smaller, which may reflect the relative scales of Uber and Lyft, the heterogeneous speeds at which the market adjusts, or both.

Finally, we shed light on the competition and substitution between taxi, Uber, and Lyft, by showing that surge multiples positively correlate with subsequent pick-ups of alternative transportation modes. In Table 4, for example, doubling UberX price predicts 2.5 more taxi trips and 0.21 more Lyft trips requested in the following 5 minutes. These effects are estimated positive and strong, even after controlling for fixed effects as granular as pickupzone-hour-weekday. However, these patterns can be driven by demand shocks that are correlated but not controlled, instead of substitution. To causally identify these effects, we conduct a formal demand estimation in Section 4.

4 Demand Estimation

4.1 Demand for Rides

Market conditions constantly change in the market of rides: factors such as prices, wait time, and conditions of competing alternatives vary at a high frequency across time within a location. Consumers make transit decisions by evaluating these relevant time-varying characteristics. Therefore, we set up the demand model at a granular route-time level, which we believe is a reasonable unit

Table 3: Dynamic Pricing Predicts Shorter Subsequent Wait Time

	$\boldsymbol{WT_{t+1}-WT_t}$	$\boldsymbol{WT_{t+2}-WT_{t+1}}$	$\boldsymbol{WT_{t+3}-WT_{t+2}}$	$\boldsymbol{WT_{t+4}-WT_{t+3}}$	$\boldsymbol{WT_{t+5}-WT_{t+4}}$
UberX Surge	-30.15***	-47.28***	-55.31***	-54.95***	-48.68***
	(0.43)	(0.51)	(0.55)	(0.58)	(0.60)
UberXL Surge	-62.26***	-100.36***	-119.17***	-118.51***	-118.51***
	(0.74)	(0.87)	(0.94)	(0.99)	(0.99)
UberSUV Surge	-16.59***	-30.28***	-41.80***	-51.47***	-51.47***
	(0.73)	(0.92)	(1.02)	(1.09)	(1.09)
UberBlack Surge	-12.74***	-22.95***	-30.85***	-37.81***	-37.81***
	(0.68)	(0.85)	(0.94)	(1.00)	(1.00)
UberPool Surge	-39.85***	-63.95***	-76.23***	-78.91***	-78.91***
	(0.68)	(0.79)	(0.86)	(0.90)	(0.90)
Lyft Surge	-16.90***	-26.88***	-33.99***	-39.32***	-39.32***
	(0.08)	(0.09)	(0.10)	(0.11)	(0.11)
LyftLine Surge	-14.35***	-23.04***	-29.28***	-34.03***	-34.03***
	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)
LyftPlus Surge	-12.14***	-19.97***	-25.97***	-30.87***	-30.87***
	(0.10)	(0.12)	(0.13)	(0.14)	(0.14)

Note: Each cell represents a regression of the first difference of wait time on the surge multiple, for a given service type and at a given minute of the next 5-minute period. For example, the first cell is the regression of the change in UberX wait time from t to $t+1$ on UberX surge multiple at time t, where the number -30.15 indicates that a 100% increase in UberX price predicts a decrease in UberX wait time in the next minute by 30.15 seconds. The fixed effects included in each regression are at the level of pickupzone-hour-weekday, where "weekday" is a set of dummies for 7 days of the week. Standard errors are in parentheses; *** stands for statistical significance at 1% level.

of analysis in this market.

Consider a scenario in which an agent i, who needs to move from location j to location k at time t, demands a ride. She faces a set of heterogeneous transportation modes: public transportation, taxi, and ride-sharing platforms. This agent evaluates these options by comparing various attributes that affect her utility, such as price, travel time, wait time, other observed and unobserved service-specific characteristics, as well as her own idiosyncratic taste. She then chooses the transportation mode that gives her the highest utility. Thus, our analysis follows the discrete choice demand framework, and the utility function is specified as

$$U_{sijkt} = -\alpha_{jkt}P_{sjkt} + \beta_{jkt}(ToT_{ojkt} - WT_{sjt} - TT_{sjkt}) + X'_{sjkt}\Theta + \xi_{sjkt} + \phi_{jkt} + \epsilon_{sijkt} \tag{1}$$

where P_{sjkt} is the price of the trip; s denotes one of the "inside options" considered in this paper: taxi and all the service types on Uber and Lyft. We treat public transportation as the outside option, which requires a total travel time of ToT_{ojkt}.[21] Let WT_{sjt} denote the wait time of s at

[21] As a key difference with the existing literature on discrete choice demand estimation, we do not allow for the no-purchasing option. We study how consumers choose from available transportation options, assuming that the trip demand is fixed.

Table 4: Dynamic Pricing Predicts More Subsequent Pick-ups

	Taxi Pick-ups	**Uber Pick-ups**	**Lyft Pick-ups**
Panel A: Next 5 Minutes			
UberX Surge Multiple	2.50***	*0.88****	0.21***
	(0.01)	*(0.01)*	(0.00)
Lyft Surge Multiple	0.77***	0.46***	*0.00****
	(0.01)	(0.00)	*(0.00)*
Panel B: Next 10 Minutes			
UberX Surge Multiple	4.78***	*1.80****	0.37***
	(0.02)	*(0.01)*	(0.00)
Lyft Surge Multiple	1.48***	0.93***	*0.06****
	(0.01)	(0.01)	*(0.00)*
Panel C: Next 15 Minutes			
UberX Surge Multiple	6.83***	*2.79****	0.55***
	(0.04)	*(0.02)*	(0.01)
Lyft Surge Multiple	2.20***	1.41***	*0.13****
	(0.02)	(0.01)	*(0.00)*

Note: Each cell represents a separate regression of the respective transportation pick-ups on the corresponding surge multiple. Note that Uber pick-ups are aggegate trip counts over all Uber service types, and the same apllies for Lyft, because TLC FHV data do not indicate trip service types. For prices, we use UberX and Lyft surge multiples, given that these two service types are the mostly used options on Uber and Lyft, respectively. Standard errors are in parentheses (*** stands for statistical significance at 1% level).

location j and time t, while TT_{sjkt} is the travel time of s. Therefore, $ToT_{ojkt} - WT_{sjt} - TT_{sjkt}$ represents the amount of time s saves compared to the outside option, and β_{jkt} is the marginal utility of time saved. Let X_{sjkt} represent a vector of observed service-specific characteristics that affect utility, Θ being the associated vector of parameters. In addition, ξ_{sjkt} is the unobserved (to the researcher) utility component; ϕ_{jkt} is the utility difference between all other service types and public transportation — it measures rider utility of not having to walk to the subway station, not finding a seat, or both; and ϵ_{sijkt} is the consumer idiosyncratic error term. The travel time TT_{sjkt} is assumed to be the same for all inside services types. As a result, the subscript s in TT_{sjkt} is removed from here on.

The market shares of service types, however, are not available at the route level in real time. As previously mentioned, this is because the ridership data of public transit do not exist at a level as granular as our route-times, which makes it impossible to compute the market shares of each of the service types. This is a great empirical challenge that we need to deal with, as existing discrete-choice demand estimation methodologies such as those of Berry [1994] and Berry et al.

[1995] do not apply in our setting.

To feasibly estimate the demand, we take advantage of the odds ratios in the logit framework to establish our identification, in a similar manner as Chevalier and Goolsbee [2009][22]. This essentially avoids the aforementioned problems caused by unavailable market shares, while at the same time flexibly allows for taste heterogeneity across markets. Specifically, we assume a Type 1 extreme value distribution of the error term, which amounts to a standard logit at each jkt cell. Normalizing the mean utility of the outside option at jkt to be 0 gives the market share of s in the market jkt:

$$MarketShare_{sjkt} = \frac{exp(\delta_{sjkt})}{1 + \sum_{n=1}^{S} exp(\delta_{sjkt})} \tag{2}$$

where $\delta_{sjkt} = -\alpha_{jkt} P_{sjkt} + \beta_{jkt}(ToT_{ojkt} - WT_{sjt} - TT_{jkt}) + X'_{sjkt}\Theta + \phi_{jkt} + \xi_{sjkt}$ is the mean conditional utility of service s at jkt. To ease illustration, let taxi cabs be denoted as c. Then taking logs of the predicted odds ratios of taxis' share and the share of any one ride-sharing service type yields

$$\begin{aligned} log(\frac{D_{cjkt}}{D_{sjkt}}) &= \alpha_{jkt}(P_{sjkt} - P_{cjkt}) + \beta_{jkt}(WT_{sjt} - WT_{cjt}) \\ &+ (X_{cjkt} - X_{sjkt})'\Theta + \xi_{cjkt} - \xi_{sjkt} \end{aligned} \tag{3}$$

where D_{cjkt} and D_{sjkt} are trip counts of taxi and service type s, respectively. Equation 3 indicates that the number of taxi trips at the route-time level should be positively correlated with the location-time prices and wait time of platform service s, and negatively correlated with the location-time own prices and own wait time, as well as differentials in other observed and unobserved characteristics.

We chose to use the simple logit framework primarily due to the benefit of analytical solutions that allow for identification in the absence of data on market shares. However, it is important to recognize the IIA (Independence of Irrelevant Alternatives) problem associated with simple logit, which puts too much weight on the idiosyncratic error in driving the substitution patterns, compared to the random coefficients models. We use as many fixed effects as the model can afford, at various levels across time and space, in an attempt to alleviate the consumer taste heterogeneity problem. Although relatively restrictive within jkt, the model allows for heterogeneous marginal utility of price and wait time across jkt's:

[22] As will be shown later, we face a new challenge of correlated errors, which is absent in Chevalier and Goolsbee [2009], who use the difference between an inside option and the outside option to establish identification.

$$\alpha_{jkt} = Y'_{jkt}\Theta_A + \epsilon_\alpha \tag{4}$$

$$\beta_{jkt} = Y'_{jkt}\Theta_B + \epsilon_\beta \tag{5}$$

where Y_{jkt} is a row vector of dummy variables that contain various combinations of pick-up areas and time blocks, and Θ_A and Θ_B are the vectors of the corresponding coefficients for price and time, respectively. Specifically, the areas include Lower Manhattan (dummy), Midtown Manhattan (dummy), Upper East and West Manhattan (dummy), and Non-Manhattan Core (dummy). Time blocks include morning rush (weekdays 7 a.m. - 9 a.m.), evening rush (weekdays 4 p.m. - 7 p.m.), weekday day time (weekdays 10 a.m. - 3 p.m.), weekday night (weekdays 8 p.m. - 11 p.m.), weekday late night (weekdays midnight - 6 a.m.), weekend day time (weekends 5 a.m. - 5 p.m.), weekend night (Friday 8 p.m. - 11 p.m. and weekends 6 p.m. - 11 p.m.), and weekend late night (weekends midnight - 4 a.m.).

Several data limitations still exist with estimation of Equation 3. First, we do not observe the wait time of taxi cabs WT_{cjt}. However, consumers do not likely know taxi wait time at a given location at a given time either. They instead act according to their expectations of WT_{cjt}. In addition, this expectation is probably rough in location and time. Therefore, the many location and time fixed effects included in the regression should be able to absorb WT_{cjt} (to be specific, $-\beta_{jkt}WT_{cjt}$ in the regression).

Another limitation is that Uber and Lyft trip records published by TLC lack drop-off information and trip service types, which prevents us from getting the trip counts of various Uber and Lyft service types at the jkt route, or D_{sjkt}. To address this issue, we use the surveyed 75,704 Uber and Lyft historical trips in the same time period to construct proxies. This sample consists of a random subsample and a convenience subsample. In the data appendix A.3, we show that the convenience subsample resembles the random subsample closely, so we can rely on the randomness of the full sample to infer D_{sjkt}. To infer D_{sjkt}, we first estimate a probit function to predict the probability of a certain trip that takes place in a certain jkt cell, using the full sample. We then infer D_{sjkt} by distributing the total Uber/Lyft pick-ups at a jt to various service types and destinations, based on these empirical probabilities.[23]

We define jkt at the level of origin-destination-15minute. Having both the origin and destination at the taxi zone level, however, leads to long-right-tailed distributions of D_{cjkt} and D_{sjkt}.

[23] A detailed discussion is presented in the data appendix A.4.

This can be especially problematic, because extremely small predicted values of D_{sjkt} can lead to extremely large odds ratios in the dependent variable, which can drive the estimates by unreasonably large variation. In other words, too much weight can be put on these extreme values due to the exponential nature. As an effort to alleviate the potential bias due to measurement error in D_{sjkt}, we use a larger geographical area defined by PUMA (Public Use Microdata Areas) as the destination unit.[24] Further, we choose to drop observations with D_{sjkt} less than 0.1, for the same concern regarding the potential measurement error in the odds ratio. Our sample then contains only $sjkt$'s where $D_{cjkt} > 0$ *and* $D_{sjkt} \geq 0.1$. Within each jkt, there are varying number of observations depending on the aforementioned filters ($D_{cjkt} > 0$ *and* $D_{sjkt} \geq 0.1$). For example, if only UberX and Lyft trips in a particular jkt are estimated at least 0.1 while taxi trips are positive, this jkt then contains two observations: one with odds ratio between taxi and UberX, and the other with odds ratio between taxi and Lyft.

4.2 Estimation and Identification

Our estimation, like other demand estimation studies, is subject to price and wait time endogeneity, given that Uber and Lyft pricing algorithms can potentially take into account many factors that affect demand, both observed and unobserved to the researchers. Then a simple OLS estimation of Equation 3 would lead to biased estimates of variables of interest.

To deal with this endogeneity, we implement an IV strategy by instrumenting for $P_{sjkt} - P_{cjkt}$ using the average surge price across the origins of all trips arriving at jt in the previous time period. On one hand, origin surge price affects the trips demanded in the origin, which then affects the number of drop-offs and available drivers at the focal location, and this in turn affects the prices adjusted at the focal location by the pricing algorithms, thus creating a correlation between the origin surge price and focal location price. On the other hand, the exclusion restriction holds in our setting due to the unique design feature of Uber and Lyft — platforms commit to a surge multiple before riders put in their destinations, as shown in Figure 1. That is, the platforms have no knowledge of where riders plan to go before committing to a price, which helps break the linkage between origin price and destination demand shock and justify the exclusion restriction.[25]

[24]There are 55 PUMA's in NYC. For a visual representation, see https://data.cityofnewyork.us/Housing-Development/Public-Use-Microdata-Areas-PUMA-/cwiz-gcty/data

[25]This might not be the case anymore given that Uber and Lyft now require riders to input their destinations before showing a fixed price for the trip. In this case, origin price can be affected by the destination demand shock, if the ride-sharing platforms practice dynamic programming and discriminate riders based on destinations. For example, the demand shock at the destination may lead the platform to willingly offer a low price at the origin, just to have the driver relocated to the destination.

Of course, it is reasonable to argue that platforms can infer the likelihood of destinations given the historical data they have, which creates an association between origins and destinations. We rely on the many location and time fixed effects to help alleviate this concern.

A similar endogeneity issue applies to WT_{sjt}, and in the same spirit, we adopt an IV strategy by exploiting the total number of drop-offs at all neighboring zones of the focal zone. This essentially measures the stock and availability of cars close to the focal zone, which affects the wait time at the focal zone, but at the same time is not likely to be influenced by focal zone demand shocks.

The stochastic unobserved utility component ξ is assumed to be normally distributed with mean zero and independent across both service types and jkt's. The error term $\xi_{cjkt} - \xi_{sjkt}$ in Equation (3), however, creates within-jkt correlation among the observations, as these observations share a common part ξ_{cjkt} in the error. Specifically, $COV(\xi_{cjkt} - \xi_{sjkt}, \xi_{cjkt} - \xi_{s'jkt}) \neq 0$ for two on-demand service types s and s' in the same jkt. Given that we use instrumental variables that are not correlated with ξ_{cjkt}, a random effects estimator would be appropriate to deal with the correlation in errors. One complication to the problem is that the analysis sample is unbalanced — as illustrated in Section 4.1, there are varying number of observations within a given jkt due to the sub-sampling filters applied ($D_{cjkt} > 0$ and $D_{sjkt} \geq 0.1$). We choose to follow the general method proposed in Balestra and Varadharajan-Krishnakumar [1987] to estimate Equation (3) by Feasible Generalized Two-Stage Least Squares.

Denote $e_{sjkt} = \xi_{cjkt} - \xi_{sjkt}$, where the variances of ξ_{cjkt} and ξ_{sjkt} are σ_c^2 and σ_s^2, respectively. Let S_{jkt} be the set of ride-sharing service types available at a particular jkt; T_{jk} is the set of time periods for a particular route jk; K_j is the set of destinations for a particular pick-up location j; J is the set of all available pick-up locations. Further denote C_{sjkt} as the number of unique $sjkt$'s and C_{jkt} as the number of unique jkt's, which are calculated by summing the cardinality the relevant sets

$$C_{jkt} = \sum_{J} \sum_{K_j} |T_{jk}| \tag{6}$$

$$C_{sjkt} = \sum_{J} \sum_{K_j} \sum_{T_{jk}} |S_{jkt}| \tag{7}$$

Then the estimator can be constructed by the following procedure:

Step 1: Estimate Equation (3) by a simple two-stage least squares regression without accounting for correlated errors, which leads to the composite residual $\hat{e}_{sjkt} = \widehat{\xi_{cjkt} - \xi_{sjkt}}$.

Step 2: Decompose the composite residual

$$\hat{\xi}_{cjkt} = \frac{1}{|S_{jkt}|} \sum_{S_{jkt}} \hat{e}_{sjkt} \tag{8}$$

and

$$\hat{\xi}_{sjkt} = \hat{e}_{sjkt} - \hat{\xi}_{cjkt} \tag{9}$$

Step 3: Compute the variance estimates $\hat{\sigma}_c^2$ and $\hat{\sigma}_s^2$, using the decomposed residuals $\hat{\xi}_{cjkt}$ and $\hat{\xi}_{sjkt}$

$$\hat{\sigma}_c^2 = \frac{1}{C_{jkt}} \sum_{J} \sum_{K_j} \sum_{T_{jk}} (\hat{\xi}_{cjkt} - \frac{1}{C_{jkt}} \sum_{J} \sum_{K_j} \sum_{T_{jk}} \hat{\xi}_{cjkt})^2 \tag{10}$$

and

$$\hat{\sigma}_s^2 = \frac{1}{C_{sjkt}} \sum_{J} \sum_{K_j} \sum_{T_{jk}} \sum_{S_{jkt}} (\hat{\xi}_{sjkt} - \frac{1}{C_{sjkt}} \sum_{J} \sum_{K_j} \sum_{T_{jk}} \sum_{S_{jkt}} \hat{\xi}_{sjkt})^2 \tag{11}$$

Step 4: Construct a $C_{sjkt} \times C_{sjkt}$ block diagonal matrix with C_{jkt} number of blocks

$$\hat{\Omega}^{-\frac{1}{2}} = \begin{bmatrix} \ddots & \mathbb{O} & \mathbb{O} \\ \mathbb{O} & \left[\hat{\mathbb{Q}}_{jkt}\right]_{|S_{jkt}| \times |S_{jkt}|} & \mathbb{O} \\ \mathbb{O} & \mathbb{O} & \ddots \end{bmatrix}_{C_{sjkt} \times C_{sjkt}} \tag{12}$$

where each block element ($\left[\hat{\mathbb{Q}}_{jkt}\right]_{|S_{jkt}| \times |S_{jkt}|}$) is a square matrix with diagonal elements equal to $\frac{1}{|S_{jkt}|}(\frac{1}{(|S_{jkt}|\hat{\sigma}_c^2 + \hat{\sigma}_s^2)^{\frac{1}{2}}} - \frac{1-|S_{jkt}|}{\hat{\sigma}_s})$ and off-diagonal elements equal to $\frac{1}{|S_{jkt}|}(\frac{1}{(|S_{jkt}|\hat{\sigma}_c^2 + \hat{\sigma}_s^2)^{\frac{1}{2}}} - \frac{1}{\hat{\sigma}_s})$. $\mathbb{O}$ are matrices of zeros.

Step 5: The random effects estimator can be constructed explicitly as

$$(\hat{\alpha}\ \hat{\beta}\ \hat{\Theta})' = (\mathbb{X}^{*'}\mathbb{Z}^*(\mathbb{Z}^{*'}\mathbb{Z}^*)^{-1}\mathbb{Z}^{*'}\mathbb{X}^*)^{-1}\mathbb{X}^{*'}\mathbb{Z}^*(\mathbb{Z}^{*'}\mathbb{Z}^*)^{-1}\mathbb{Z}^{*'}\mathbb{D}^* \tag{13}$$

where $\mathbb{Z}$ denotes the matrix that contains all the instruments, and

$$\mathbb{X} = \begin{bmatrix} \vdots & \vdots & \vdots \\ P_{sjkt} - P_{cjkt} & WT_{sjt} - WT_{cjt} & (X_{cjkt} - X_{sjkt})' \\ \vdots & \vdots & \vdots \end{bmatrix}$$

$$\mathbb{D} = \begin{bmatrix} \vdots \\ log(\frac{D_{cjkt}}{D_{sjkt}}) \\ \vdots \end{bmatrix}$$

$$\mathbb{X}^* = \hat{\Omega}^{-\frac{1}{2}}\mathbb{X}$$
$$\mathbb{D}^* = \hat{\Omega}^{-\frac{1}{2}}\mathbb{D}$$
$$\mathbb{Z}^* = \hat{\Omega}^{-\frac{1}{2}}\mathbb{Z}$$

5 Estimation Results and Discussion

5.1 Estimation Results

We drop airport pick-ups from the sample because only very few trips end in neighboring zones of airports, and the correlation between these trips and airport wait time is very weak to justify the use of the wait time IV. To-airport trips, however, are kept in the sample. We then include two dummy variables, "to-airport" and "rain", in the vector Y_{jkt} to allow consumers on trips to the airport and trips in the rain, respectively, to have differential price and time sensitivities. The vector of observed characteristics X_{sjkt} includes luxury and capacity. Luxury measures the units of luxury service provided by the trip, which is a dummy variable on UberBlack and UberSUV, multiplied by the duration of the jkt trip. Capacity is defined similarly, except for service types UberXL, UberSUV, and LyftPlus. Finally, the set of fixed effects includes pick-up zone, drop-off PUMA, pick-up hour by weekend (dummy), pick-up PUMA by time block, pick-up PUMA by drop-off borough, and drop-off PUMA by time block. Table 8 summarizes the sample at the pickupzone-dropoffpuma-month-day-hour-15min, or jkt, level.

The results are shown in Table 9. Across almost all location-time-block combinations, the price effects on utility are estimated to be significantly negative ($-\alpha_{jkt}$) and marginal utility of time

(β_{jkt}) is estimated positive and strong, providing direct evidence that price-sensitive consumers value their time and dislike waiting. If one constructs a variable by the ratio of β_{jkt} and α_{jkt}, the median of the distribution (weighted by trip volume in each of those location-time cells) is $3, which measures the monetary value a representative consumer attaches to one minute of waiting. This result is sensible, primarily due to selection — consumers who ride taxis, ride-sharing platforms, or both are a richer subset of the NYC population. In addition, how much consumers dislike waiting also depends on the disutility of waiting, the opportunity cost of being late, and so on.

More interestingly, sensible heterogeneity is found in these estimates. For example, consumers in Midtown Manhattan during morning rush hours tend to be more time-sensitive and less price-sensitive, compared to consumers in most other location-times. This may reflect the preference of relatively high-income workers who rush into their workplaces on weekday mornings. A very similar pattern appears in Lower Manhattan during evening rush hours, which may be driven by Wall Street workers. Also, consumers going to the airport value time more and are additionally less sensitive to price. In addition, the coefficient estimates of luxury and capacity are strong, indicating that NYC consumers value these features that are made conveniently available on the platforms compared to the offline options.

5.2 Robustness Checks

As discussed in the previous section, the unique design feature of the ride-sharing applications helps rationalize the use of our instrumental variable. It should be noted, however, that other endogeneity channels may be present and cannot be eliminated by this design feature. Although we control for many location and time fixed effects to alleviate the problem, it is nonetheless difficult to clear all endogeneity problems.

One possible endogeneity threat is unobserved common demand and supply shocks that simultaneously affect origins and destinations, therefore creating a correlation between destination demand shocks and origin prices. However, this identification threat is likely more relevant for origins and destinations that are relatively close in space, time, or both. As a robustness check, we calculated the average trip duration for all trips ending in the focal zone, and split the sample by dropping observations with an average duration (of incoming trips) below the 25th percentile and 50th percentile. We found qualitatively similar results. With a similar argument, trips in Manhattan are more subject to this identification threat because they are usually short trips. Hence, in another robustness check, we only kept observations in the outer boroughs for the analysis and the results were reassuring as well.

5.3 Discussion

5.3.1 Demand Elasticities

Own-price and cross-price elasticities are generally key measures in demand studies to characterize consumer preference. These measures are not derived in this paper, because of data unavailability of market shares. However, the issue is less severe than it seems, because wait time, which affects demand, is determined simultaneously with price. Any change in price will likely lead to a change in wait time and have an extra effect on the mean conditional utility, through the effect of wait time on utility. In particular, the price elasticity can be written as:

$$\frac{\partial MarketShare(P, WT)}{\partial P} = \frac{\partial MarketShare(P, WT)}{\partial P}\Big|_{WT=WT^0} + \frac{\partial MarketShare(P, WT)}{\partial WT}\frac{\partial WT}{\partial P}$$

Although the demand estimation produces estimates on consumers' marginal utility of price ($\frac{\partial MarketShare(P,WT)}{\partial P}\big|_{WT=WT^0}$) and marginal utility of wait time ($\frac{\partial MarketShare(P,WT)}{\partial WT}$), the marginal effect of price on wait time ($\frac{\partial WT}{\partial P}$) is unknown. Notice that how wait time is affected by price is not controlled by the platforms. Instead, it is an outcome of a matching process, where the price change leads to real-time adjustments in supply and demand, which in turn affects the wait time. The new change in wait time further causes a feedback effect on demand and price, which induces yet another round of adjustments. Examining this complex feedback loop is beyond the scope of this paper. A similar decomposition applies to the cross-price elasticities of demand.

5.3.2 Endogenous Choice Set

One implicit assumption for our demand estimation procedure is that individuals multi-home on both Uber and Lyft platforms. In other words, we assume that consumers have complete information on the choice set. This may not be perfectly realistic, because there are individuals who do not yet adopt these ride-sharing platforms, and many who adopt them may not multi-home.

However, this problem might not be as severe as it seems given that our sample period is June 2016, by which Uber and Lyft had grown substantially. Based on TLC data, the number of unique vehicles dispatched by Uber in NYC had doubled the number of taxis by June 2016, and Lyft was only slightly short of the taxi medallion number.[26] A survey conducted by PEW Research Center [27] at the end of 2015 reveals that more than 20% of urban Americans have used ride-hailing applications, and over half of all Americans were familiar with these services although they had never used them. The report also indicates that the adoption of ride-hailing applications is more popular among young adults in urban areas who are more educated and relatively affluent. NYC population fits the profile in the report to have high adoption and usage of ride-sharing platforms.

There is a strand of literature that focuses on the variable choice set in the demand estimation, such as Bruno and Vilcassim [2008]. A complication with our setting is that the limited choice set is due to consumers' endogenous platform adoption decisions, rather than to exogenous reasons such as store stock-outs. Therefore, the single-homing decisions also reflect some platform-specific utility that cannot be captured by the current framework. Without consumer-level data, these consumer multi-homing and selection issues require a heavy structure that is beyond the scope of this paper.

5.3.3 Zero Sales Problem

Naturally, there are many jkt's with zero taxi trips, zero ride-sharing trips, or both zero taxi trips and zero ride-sharing trips, when jkt's are defined as finely as 15-minute intervals (Table 1). This is a frequent phenomenon across many markets of differentiated goods and services, and the measurement errors in market shares can undermine the standard discrete choice demand models for that these models always predict positive market shares (Gandhi et al. [2013], Quan and Williams [2016]). Methodologies that mitigate this problem are limited and require certain assumptions on the number of products, consumers, or both within a market. For example, the proposed solution of Gandhi et al. [2013] uses a system of moment inequalities implied by demand shape restrictions, but crucially relies on a large number of differentiated products. This, however, is a poor description of the market for rides. Another way to alleviate the zero sales problem is to aggregate the data to coarser jkt levels. But this practice would defeat the purpose of this study, which aims to estimate the real-time demand. While recognizing the potential selection bias, we decide to drop all service types with zero sales at jkt.

[26]See http://toddwschneider.com/posts/taxi-uber-lyft-usage-new-york-city/

[27]http://www.pewinternet.org/2016/05/19/on-demand-ride-hailing-apps/

6 Taxi Market Equilibrium

Since the purpose of this paper is to study consumer welfare gain by a counterfactual with no ride-sharing platforms, it is important to understand how taxis would respond in this situation. In this section, we propose a model of taxi market equilibrium. The uniqueness of the taxi market, well articulated in Orr [1969], is the difference between operating hours and passenger service units supplied: taxi drivers' costs depend on the hours of driving and searching for passengers, while their revenues depend on the fare multiplied by the number of passenger service units supplied. This is due to the nature of the taxi matching technology. Here, we modify the framework used in Orr [1969] to fit our purpose. Let the taxi demand be specified as,

$$D = f(F^a, q; M, \Theta_D)$$

where D is the number of passenger service units demanded; F^a is the fixed administered fare; q is the total operating hours of taxi drivers; M is the number of potential consumers; and Θ_D is a vector of demand parameters. Also, D is continuous in F^a and $\frac{\partial D}{\partial F^a} < 0$; D is continuous in q, and $\frac{\partial D}{\partial q} > 0$, because as more taxi hours are provided, consumers are more quickly matched to drivers and the average consumer wait time decreases; and $D(q = 0, F^a; M, \Theta_D) = 0$, $\frac{\partial D}{\partial q}\Big|_{q=0} >> 0$, $\frac{\partial^2 D}{\partial q \partial q} < 0$, and $\frac{\partial^2 D}{\partial q \partial M} > 0$.

The taxi market is a market with a rather elastic supply of labor; only modest skills are required to operate taxi cabs, and the practice of daily lease of medallions to the drivers imposes quite low entry and exit costs.[28] Cab drivers respond positively to wage increases by working longer hours (Chen and Sheldon [2016], Farber [2015], Hall et al. [2017]). Under competitive conditions, the market equilibrium is characterized as a steady state where marginal cost and average revenue are equalized:

$$\frac{F^a * D(F^a, q; M, \Theta_D)}{q} = MC(q) \tag{14}$$

where $MC(q)$ is the marginal cost of operating a taxi, $MC(q) > 0$, $MC(q) << \infty$, $\frac{\partial MC}{\partial q} \geq 0$, and $\frac{\partial^2 MC}{\partial q \partial q} \geq 0$. The fixed medallions impose a hard constraint on the number of operating hours available in the market, that is, the maximal amount of daily operating hours is the number of medallions multiplied by 24 hours. Let this maximum be $\bar{q}$. Then the algebra leads to that the

[28] Farber [2015] documents "a fair amount of entry, exit, and reentry among taxi drivers". Hall et al. [2017] demonstrate the horizontal labor supply curve for Uber drivers, which may as well be the case for cab drivers.

equilibrium operating hours supplied is concave in D up till $\bar{q}$. [29]

Let wait time for taxi riders be defined as,

$$WT = f(q, D; \Theta_{WT})$$

where WT is a continuous function, twice differentiable in q and D, with parameters denoted by the vector Θ_{WT}. Particularly, $\frac{\partial WT}{\partial q} < 0$ and $\frac{\partial^2 WT}{\partial q \partial q} > 0$: holding other things constant, more taxi service supplied leads to less wait time for consumers, yet this decrease in wait time diminishes as service units increase. $\frac{\partial WT}{\partial D} > 0$ and $\frac{\partial^2 WT}{\partial D \partial D} > 0$: holding other things constant, more trips demanded lead to longer consumer wait time, and this increase in wait time is greater as more trips are demanded.

A graphical characterization of the taxi market equilibrium is presented in Figure 5a, where the equilibrium path is the combination of the part of q^* before $\bar{q}$ and the part of vertical line above q^* (the curve in red). An immediate implication on the equilibrium service units and equilibrium taxi wait time is depicted qualitatively in Figure 5b — wait time increases as equilibrium service units increase after the capacity constraint. This is because supply cannot further adjust after the capacity constraint. Therefore, $\frac{\partial WT}{\partial D*} = \frac{\partial WT}{\partial q*}\frac{\partial q*}{\partial D*} + \frac{\partial WT}{\partial D} = 0 + \frac{\partial WT}{\partial D} > 0$.[30] The intuition is simple: as demand increases and maximal taxi capacity is reached, more and more consumers compete with each other to get matched to a fixed number of operating taxi cabs, which leads to longer average consumer wait time.[31]

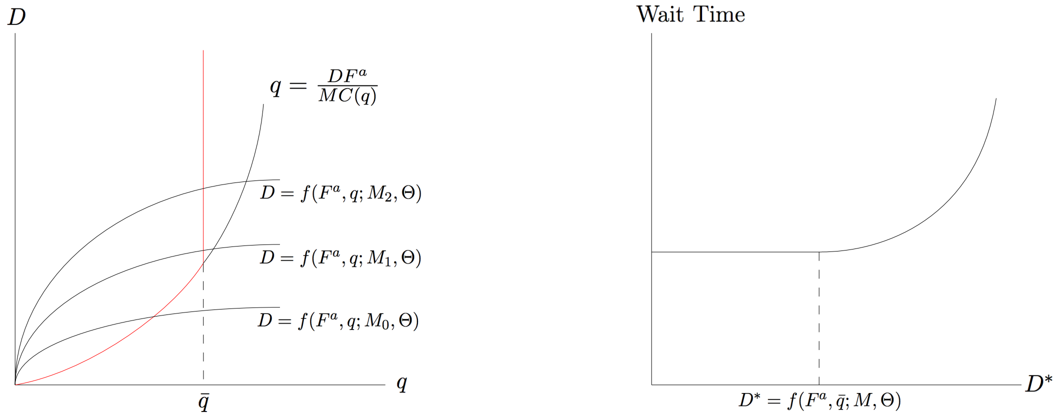
One direct way to test the model prediction is to do a scatter plot of taxi pick-ups with taxi wait time, and check whether the empirical pattern resembles Figure 5b. Unfortunately, in this study we do not observe, estimate, or simulate the actual taxi wait time. However, Frechette et al. [2016] are able to simulate taxi wait time from observed taxi cabs, taxi search time, and exogenous time-varying factors, combined with a simulated matching function (Figure 6 of their paper). We contrast their wait time estimates with UberTaxi wait time from our API queries in Figure 6, and

[29] Differentiating both sides of Equation 14 with respect to D leads to $\frac{\partial q}{\partial D} = \frac{F^a}{MC(q) + \frac{\partial MC}{\partial q} q} > 0$. Then $\frac{\partial^2 q}{\partial D \partial D} = -\frac{F^a \frac{\partial q}{\partial D}[2MC'(q) + MC''(q)q]}{[MC(q) + \frac{\partial MC}{\partial q} q]^2} < 0$.

[30] Before the capacity constraint $\bar{q}$, the term $\frac{\partial WT}{\partial q*}\frac{\partial q*}{\partial D*}$ is negative, so the sign of $\frac{\partial WT}{\partial D*}$ is undetermined. We use a flat line in Figure 5b to describe the relationship between q and D before $\bar{q}$, but it should be noted that this relationship can be either positive, zero, or negative.

[31] Note that the market equilibrium proposed here abstracts away from the spatial equilibrium models such as Lagos [2000], Lagos [2003], and Buchholz [2015]. It is possible that when there is an exogenous shock of demand, taxi cabs relocate spatially and form a new spatial equilibrium, which results in a different average wait time than implied by our model.

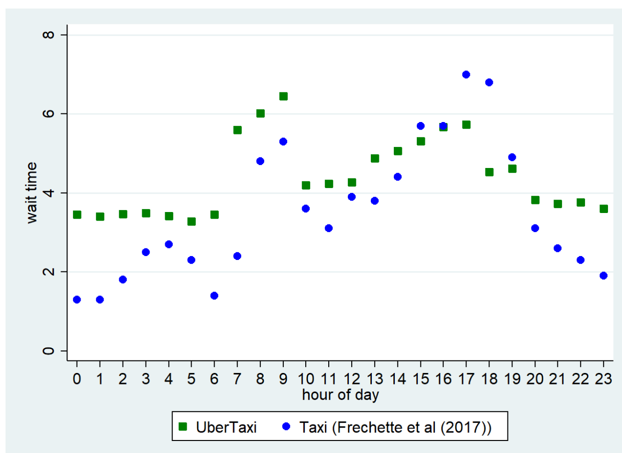
Figure 5: Taxi Market Clearing



(a) Taxi Market Equilibrium

(b) Model Prediction of Equilibrium Service Units and Wait Time

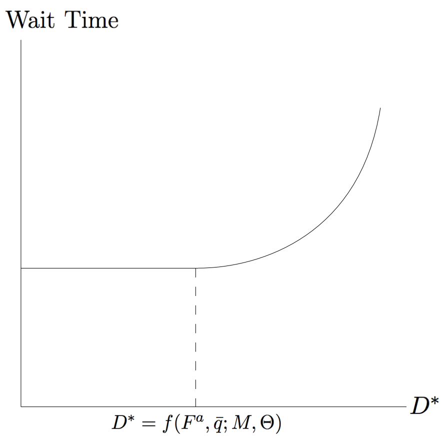
Figure 6: UberTaxi Wait Time and Taxi Wait Time from Frechette et al. [2016]



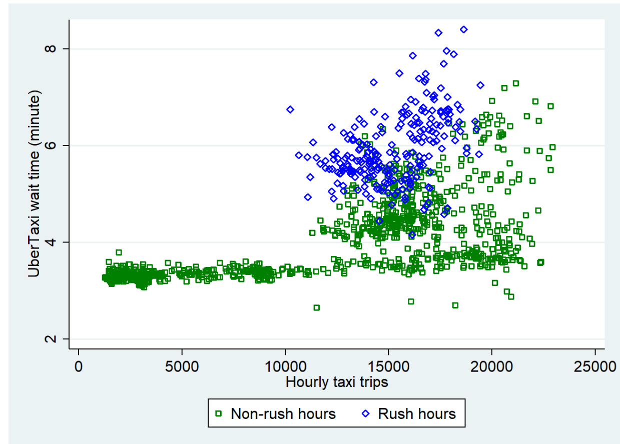
find that UberTaxi wait time follows a similar trend as their estimates across hours of day, although UberTaxi wait time is less volatile. We believe that UberTaxi is a reasonable proxy for taxi wait time and use it in the test of the taxi market equilibrium.

The data strongly support the model prediction, as shown in Figure 7b. Overall, there is a positive correlation between taxi trips and wait time. In particular, the average wait time is relatively low below some trip quantity threshold but becomes much higher after the threshold with a greater variation. In addition, there is a sharp contrast between rush hours and non-rush hours: first, rush hour wait time is on average higher; and second, the correlation between trip volume and wait time after the threshold at 10,000 trips, is greater during rush hours (correlation coefficient is 0.42) than non-rush hours (correlation coefficient is 0.19). This is likely due to the certain

Figure 7: Taxi Trips and Taxi Wait Time



(a) Model Prediction of Equilibrium Service Units and Wait Time



(b) Hourly Taxi Wait time and Taxi Trips in Manhattan Core, Weekdays

spatial distribution of commuting routes during rush hours, which exacerbates the within-location imbalance of demand and supply. We leverage these empirical correlations in the counterfactual analysis.

7 Consumer Welfare Calculation

To evaluate the consumer surplus of the ride-sharing platforms, we follow the concept of compensating variation. In other words, how much should consumers be compensated if Uber and Lyft were to be removed from the market such that the consumers can maintain the same level of utility? In the counterfactual, we assume that taxi and subway [32] are the only viable options. We further assume that the subway remains the same operation, without capacity constraint when more riders substitute toward it. For taxis, we consider two sensible counterfactual strategies.

7.1 Benchmark Counterfactual

In the first counterfactual analysis, the taxi system remainswith the current fixed number of medallions and administered fares. There are two major reasons why consumers would be made worse off in the absence of ride-sharing services: first, existing ride-sharing users would lose all the amenities from ride-sharing services which they value more than other alternatives, due to revealed preference (that is, they would not have used ride-sharing services had these services not provided the users

[32] The outside option — the public transit — should include buses as well. But due to data limitation on route-specific bus travel time, we focus only on the subway system in the counterfactual study.

with the highest utility); second, as shown in Section 6, when more consumers willingly substitute toward taxis, the equilibrium average wait time increases, which makes existing taxi users worse off.

To feasibly calculate the compensating variation and disentangle the various welfare mechanisms, we compute the mean conditional utility of taxi and subway at jkt to predict how consumers would substitute in the absence of ride-sharing services. In this exercise, we use the taxi wait time estimates of Frechette et al. [2016] as the counterfactual taxi wait time. One key component missing from the demand estimation is ϕ_{jkt}, the utility difference between all car service types and the subway. Recall the demand function:

$$U_{sijkt} = -\alpha_{jkt}P_{sjkt} + \beta_{jkt}(ToT_{ojkt} - WT_{sjt} - TT_{jkt}) + X'_{sjkt}\Theta + \xi_{sjkt} + \phi_{jkt} + \epsilon_{sijkt}$$

where ϕ_{jkt} did not pose a problem in the demand estimation, since it is common across all service types except the outside option and thus differenced out in the estimation. The term ϕ_{jkt} is the product of the constant per-unit utility ϕ and jkt-specific duration. Without any knowledge of ϕ, we cannot appropriately assign consumers into taxis and subway in the counterfactual. However, we have estimated the utility of luxury in the demand and can use it as a reference, because a consumer's utility of sitting in a car and not having to walk to a subway station can be proportional to the utility of sitting in a luxury car. In fact, ϕ can be multiples of luxury utility due to diminishing marginal utility of sitting — being able to sit means more utility than sitting comfortably. We further allow for rush hours to differ from non-rush hours to account for the extra disutility of riding the subway during rush hours, and this unknown constant multiple is denoted as ϕ^r.

In the search for ϕ and ϕ^r, we rely on the fact that once Uber and Lyft are removed from the market, the number of taxi trips will increase because of sheer substitution. That is, the values of ϕ and ϕ^r must be such that the corresponding counterfactual taxi ridership is greater than or equal to the current ridership. It is important to note that using this boundary equality (counterfactual ridership is equal to current ridership) leads to conservative estimates of ϕ and ϕ^r, given the monotonic relationship between these values and consumers' preference for taxis, which then leads to a conservative estimate of taxi wait time change and a lower bound for the welfare estimate.

After we get the lower-bound estimates for ϕ and ϕ^r that satisfy the above-mentioned criterion, we can calculate the welfare. One key problem is then to compute the taxi wait time in the current world with ride-sharing platforms, which is neither observed nor estimated in the demand. This is where we use the empirical relation between UberTaxi wait time and taxi trips in Figure 7 (b). Specifically, we perform an OLS regression on the following model separately for rush hours and non-rush hours, on day-hours when taxi trips exceed the capacity threshold 10,000:

$$\textit{Taxi wait time} = \pi_0 + \pi_1 \textit{Taxi trips (1,000s)} \tag{15}$$

where π_1 is estimated at 0.155 for rush hours (N=233, t=7.09), and at 0.057 for non-rush hours (N=559, t = 4.51). The estimated coefficients, counterfactual wait time, counterfactual taxi trips, and current taxi trips help us compute the current taxi wait time. For example, for rush hours,

$$\textit{current wait time} = \textit{0.155*(current taxi trips - counterfactual taxi trips)} + \textit{counterfactual wait time} \tag{16}$$

With the inferred taxi wait time, we compute the current utility of taxi riders and their counterfactual utility of riding taxis, conditional on that they still choose taxis in the counterfactual. This gives us the competition effect for that it measures how consumers are made better off by the entry of ride-sharing platforms, which reduces the wait time of taxi riders. At the same time, we also compute the utility difference of current ride-sharing users by comparing their current options with counterfactual best options. We further break down the total surplus into distinct amenities in the demand and show the relative contribution of these amenities.

Column 1 of Table 10 summarizes the benchmark counterfactual results: the consumer surplus per dollar spent on these ride-sharing services is about 72 cents, or $14 for an average trip. We further break these welfare measures into distinct welfare channels, namely price, time, luxury, and capacity, and we find the vast majority of the consumer surplus comes from better accessibility (shortened wait time), compared to taxis and the subway. Another important welfare source is the convenient availability of luxury cars that are valued in NYC. A very thin share of the consumer welfare increase comes from price, yet this is not surprising since in NYC, Uber and Lyft prices overall compare to taxi prices at the base-price level. As a sizable supplement to the public transit, Uber and Lyft provide car services that increase consumer surplus with more comfortable seating and traveling (13% of total consumer surplus). We further compare the per-dollar welfare across service types, pick-up boroughs, and rush and non-rush hours, and find a good deal of heterogeneity across these splits. In particular, the per-dollar consumer surplus is higher in the outer boroughs than in Manhattan, which is expected given that alternative options are more conveniently available in Manhattan. Likewise, Uber and Lyft generate proportionally more welfare gain during rush hours than during non-rush hours, primarily due to the high utilization and poor performance of taxis and subway in rush hours. Finally, taxi riders gain 16 cents per dollar spent, because taxi wait time becomes shorter as a result of consumer substitution toward ride-sharing platforms. Similar benefits to users of incumbent goods or services due to lower prices (as a result of competition) are documented in the literature, such as consumers of automobiles (Petrin [2002]), cable TV (Goolsbee and Petrin [2004]), and hotels (Farronato and Fradkin [2017]), except that here the benefit comes from shorter queuing time.

7.2 Application-based Taxis

What factors account for the substantial welfare improvement seen in the benchmark counterfactual? A commonly held view is that ride-sharing platforms are merely taxis with an app, meaning that the main (if not only) differentiator is the matching technology used. Many others instead consider dynamic pricing as the driving force of the economic value. In this section, we make an attempt to evaluate the relative importance of these two mechanisms by studying a counterfactual where taxis adopt the same (or similar) app-based matching technology.[33] The rationale is that the additional consumer surplus due to entry of ride-sharing platforms, when the matching technology is already in place, would largely reflect the value of dynamic pricing.

In this counterfactual, the medallion system remains capped and cab fares are fixed at the current rate. The app essentially dispatches a cab to any rider requesting a ride on a first-come-first-serve basis. We are well-equipped to study this counterfactual since we have wait time data of UberTaxi, which the counterfactual taxis greatly resemble. Therefore, we proxy the counterfactual taxi wait time by UberTaxi wait time, avoiding the heavy structure that requires modeling the optimal dispatching process and the resulting wait time. Although UberTaxi offers a great deal of valuable convenience, it should be noted that the true counterfactual taxi wait time depends on the extent of app adoptions by both drivers and riders, which can be rather different than UberTaxi adoptions.

We follow roughly the same procedure as laid out in the benchmark counterfactual and present the results in Column 2 of Table 10. Compared with the benchmark case, consumer surplus of Uber and Lyft is generally less when taxis adopt the application-based matching, around 46 cents

[33] In fact, NYC TLC has partnered with private enterprises to launch the smartphone application Arro, which matches cab drivers with riders at no additional cost.

per dollar. To the extent that the unique nature of ride-sharing platforms is the application-based matching combined with dynamic pricing, this counterfactual result helps us learn the value added of dynamic pricing, which takes a significant share of the total benchmark consumer surplus. More interestingly, we compare the per-dollar welfare gain across NYC boroughs and find that this measure is greater in Manhattan ($0.51) than in outer boroughs ($0.12- $0.34). This further speaks to the benefit of dynamic pricing, which is likely more welfare-enhancing in thick markets with volatile demand and supply that need to be efficiently matched. In other words, the dispatching technology benefits the outer boroughs more than it benefits Manhattan.

This is consistent with the theoretical work of Castillo et al. [2017], who argue that surge pricing is critical to ride-hailing apps in efficient allocation of capacity, essentially preventing the system from reaching a catastrophic "wild goose chase" equilibrium when demand is high. In their model, surge pricing solves the problem by reducing the demand with a high price and keeping driver earnings sufficiently high. Our data provide supporting evidence: high surge predicts shorter subsequent wait time and more subsequent matches of drivers and riders.

8 Conclusion

The rise of ride-sharing platforms has promoted heated debates on many issues, and this calls for thorough evaluations of the market to guide policy decisions. Focusing on the consumer side, this paper finds strong support for the consumer welfare gain of these ride-sharing platforms. The vast majority of the surplus is due to shortened wait time, which is likely a result of the better matching technology and the practice of dynamic pricing.

Ride-sharing platforms are not simply taxis with an app. These welfare gains are unique to the tech-aided platforms to the extent that the highly regulated taxi system cannot implement dynamic pricing. We show evidence that the most important margin lies in the complementarity between the technology and dynamic pricing, which has likely contributed to the success of these platforms.

While in this paper we only used data from NYC, the welfare estimates can help infer the economic impacts of ride-sharing platforms in other cities and regions as well. This is because NYC is not just Manhattan — it consists of many neighborhoods that vary in demographics as well as transportation accessibility. This variation can help relate NYC neighborhoods to a wide range of US cities with similar configurations. However, it should be noted that our results in general imply a lower bound of welfare gain, given that NYC taxis and public transit are among the nation's best.

References

Sinan Aral, Erik Brynjolfsson, and Lynn Wu. Three-way complementarities: Performance pay, human resource analytics, and information technology. *Management Science*, 58(5):913–931, 2012.

J Yannis Bakos. Reducing buyer search costs: Implications for electronic marketplaces. *Management Science*, 43(12):1676–1692, 1997.

Yannis Bakos. The emerging role of electronic marketplaces on the internet. *Communications of the ACM*, 41(8):35–42, 1998.

Pietro Balestra and Jayalakshmi Varadharajan-Krishnakumar. Full information estimations of a system of simultaneous equations with error component structure. *Econometrics Theory*, 3(2): 223–246, 1987.

Steven Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pages 841–890, 1995.

Steven T Berry. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262, 1994.

Hemant K Bhargava and Vidyanand Choudhary. Economics of an information intermediary with aggregation benefits. *Information Systems Research*, 15(1):22–36, 2004.

Timothy F Bresnahan, Erik Brynjolfsson, and Lorin M Hitt. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, 117(1):339–376, 2002.

Hernán A Bruno and Naufel J Vilcassim. Research notestructural demand estimation with varying product availability. *Marketing Science*, 27(6):1126–1131, 2008.

Erik Brynjolfsson and Michael D Smith. Frictionless commerce? a comparison of internet and conventional retailers. *Management Science*, 46(4):563–585, 2000.

Erik Brynjolfsson, Yu Hu, and Michael D Smith. Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management Science*, 49 (11):1580–1596, 2003.

Erik Brynjolfsson, Yu Hu, and Duncan Simester. Goodbye pareto principle, hello long tail: The effect of search costs on the concentration of product sales. *Management Science*, 57(8):1373–1386, 2011.

Nicholas Buchholz. Spatial equilibrium, search frictions and efficient regulation in the taxi industry. Technical report, Working paper, 2015.

Gordon Burtch, Seth Carnahan, and Brad N Greenwood. Can you gig it? an empirical examination of the gig-economy and entrepreneurial activity. 2016.

Juan Camilo Castillo, Dan Knoepfle, and Glen Weyl. Surge pricing solves the wild goose chase. In *Proceedings of the 2017 ACM Conference on Economics and Computation*, pages 241–242. ACM, 2017.

M Keith Chen and Michael Sheldon. Dynamic pricing in a labor market: Surge pricing and flexible work on the uber platform. In *EC*, page 455, 2016.

M Keith Chen, Judith A Chevalier, Peter E Rossi, and Emily Oehlsen. The value of flexible work: Evidence from uber drivers. Technical report, National Bureau of Economic Research, 2017.

Judith Chevalier and Austan Goolsbee. Are durable goods consumers forward-looking? evidence from college textbooks. *The Quarterly Journal of Economics*, 124(4):1853–1884, 2009.

Peter Cohen, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. Using big data to estimate consumer surplus: The case of uber. Technical report, National Bureau of Economic Research, 2016.

Judd Cramer and Alan B Krueger. Disruptive change in the taxi business: The case of uber. *The American Economic Review*, 106(5):177–182, 2016.

Fred D Davis. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, pages 319–340, 1989.

William H DeLone and Ephraim R McLean. Information systems success: The quest for the dependent variable. *Information Systems Research*, 3(1):60–95, 1992.

Liran Einav, Chiara Farronato, and Jonathan Levin. Peer-to-peer markets. *Annual Review of Economics*, 8:615–635, 2016.

Henry S Farber. Why you cant find a taxi in the rain and other labor supply lessons from cab drivers. *The Quarterly Journal of Economics*, 130(4):1975–2026, 2015.

Chiara Farronato and Andrey Fradkin. The welfare effects of peer entry in the accommodations market: The case of airbnb. Technical report, Working paper, 2017.

Andrey Fradkin. Search, matching, and the role of digital marketplace design in enabling trade: Evidence from airbnb. 2017.

Guillaume R Frechette, Alessandro Lizzeri, and Tobias Salz. Frictions in a competitive, regulated market evidence from taxis. 2016.

Amit Gandhi, Zhentong Lu, and Xiaoxia Shi. Estimating demand for differentiated products with error in market shares. Technical report, cemmap working paper, Centre for Microdata Methods and Practice, 2013.

Anindya Ghose and Sang Pil Han. Estimating demand for mobile applications in the new economy. *Management Science*, 60(6):1470–1488, 2014.

Jing Gong, Brad N Greenwood, and Yiping Song. Uber might buy me a mercedes benz: An empirical investigation of the sharing economy and durable goods purchase. 2017.

Austan Goolsbee and Amil Petrin. The consumer gains from direct broadcast satellites and the competition with cable tv. *Econometrica*, 72(2):351–381, 2004.

Brad N Greenwood and Sunil Wattal. Show me the way to go home: An empirical investigation of ride sharing and alcohol related motor vehicle homicide. *MIS Quarterly*, 41(1), 2017.

Harish Guda and Upender Subramanian. Strategic surge pricing on on-demand service platforms trade: Evidence from airbnb. 2017.

Jonathan Hall, Cory Kendrick, and Chris Nosko. The effects of ubers surge pricing: A case study. *The University of Chicago Booth School of Business*, 2015.

Jonathan Hall, John Horton, and Daniel Knoepfle. Labor market equilibration: Evidence from uber. 2017.

Jonathan V Hall and Alan B Krueger. An analysis of the labor market for ubers driver-partners in the united states. Technical report, National Bureau of Economic Research, 2016.

Ricardo Lagos. An alternative approach to search frictions. *Journal of Political Economy*, 108(5): 851–873, 2000.

Ricardo Lagos. An analysis of the market for taxicab rides in new york city. *International Economic Review*, 44(2):423–434, 2003.

Ziru Li, Yili Hong, and Zhongju Zhang. An empirical analysis of on-demand ride sharing and traffic congestion. 2016.

Aviv Nevo. Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The RAND Journal of Economics*, pages 395–421, 2000.

Aviv Nevo. Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69(2): 307–342, 2001.

Daniel Orr. The "taxicab problem": A proposed solution. *Journal of Political Economy*, 77(1): 141–147, 1969.

Jiyong Park, Junetae Kim, Min-Seok Pang, and Byungtae Lee. Offender or guardian? an empirical analysis of ride-sharing and sexual assault. 2017.

Geoffrey G Parker and Marshall W Van Alstyne. Two-sided network effects: A theory of information product design. *Management science*, 51(10):1494–1504, 2005.

Amil Petrin. Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy*, 110(4):705–729, 2002.

Thomas W Quan and Kevin R Williams. Product variety, across-market demand heterogeneity, and the value of online retail. 2016.

Prasanna Tambe, Lorin M Hitt, and Erik Brynjolfsson. The extroverted firm: How external information practices affect innovation and productivity. *Management Science*, 58(5):843–859, 2012.

Georgios Zervas, Davide Proserpio, and John W Byers. The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Journal of Marketing Research*, 2014.

Shunyuan Zhang, Dokyun Lee, Param Vir Singh, and Kannan Srinivasan. How much is an image worth? airbnb property demand estimation leveraging large scale image analytics. 2017.

Zhe Zhang and Beibei Li. A quasi-experimental estimate of the impact of p2p transportation platforms on urban consumer patterns. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1683–1692. ACM, 2017.

Table 5: Uber and Lyft Dynamic Pricing and Wait Time

Variable	Mean	Std. Dev.	Min	Max	N
Surge Frequency					
UberX	0.073	0.260	0	1	32398537
UberXL	0.072	0.259	0	1	32398537
UberBlack	0.012	0.112	0	1	32359662
UberSUV	0.013	0.114	0	1	32421149
UberPool	0.080	0.272	0	1	32359652
Lyft	0.180	0.384	0	1	31257800
LyftLine	0.180	0.384	0	1	31257800
LyftPlus	0.180	0.384	0	1	31257800
Surge Multiple					
UberX	1.037	0.1622	1	4.2	32398537
UberXL	1.037	0.1619	1	4.2	32398537
UberBlack	1.008	0.0856	1	2.9	32359662
UberSUV	1.008	0.0884	1	2.9	32421149
UberPool	1.022	0.1028	1	3.4	32359652
Lyft	1.100	0.2727	1	5.0	31257800
LyftLine	1.100	0.2727	1	5.0	31257800
LyftPlus	1.100	0.2727	1	5.0	31257800
Wait Time (minutes)					
UberX	6.949	8.912	1	45	32421149
UberXL	13.509	14.794	1	45	32421149
UberBlack	8.821	10.176	1	45	32421149
UberSUV	14.059	15.324	1	45	32421149
UberPool	7.496	9.870	1	45	32421149
Lyft	7.034	9.882	1	45	33133051
LyftLine	6.884	9.869	1	45	33133051
LyftPlus	9.510	9.993	1	45	33133051

Note: The data for this table come from Uber and Lyft API queries, June-August 2016, where both price and wait time of 263 NYC zones are queried in approximately one-minute intervals. The small variation in variable sizes reflects rare cases of missing values and/or duplicated queries. There is no variation in surge frequency or surge multiples across service types within Lyft platform.

Table 6: NYC Taxi Trips Records

Variable	Mean	Std. Dev.	Min	Max	N
Trip duration (minutes)†	14.378	11.436	1	180	47483432
Trip distance (miles)	2.985	3.515	0.01	199	47483432
Base fare	12.858	10.039	0	314	47483432
Extra fee	0.337	0.435	0	21.5	47483432
MTA tax	0.498	0.023	0	2.34	47483432
Tip	1.685	2.267	0	300	47483432
Tolls	0.270	1.249	0	111.65	47483432
Improvement fee	0.299	0.011	0	0.6	47483432
Total fare	15.955	12.293	2.54	360.34	47483432
Passenger count	1.631	1.283	0	9	47483432
Yellow taxi	0.887	0.315	0	1	47483432
Manhattan pickup	0.850	0.356	0	1	47483432
Queens pickup	0.084	0.277	0	1	47483432
Bronx pickup	0.005	0.074	0	1	47483432
Brooklyn pickup	0.060	0.237	0	1	47483432
Staten Island pickup	0.000	0.006	0	1	47483432
Manhattan dropoff	0.827	0.377	0	1	47483432
Queens dropoff	0.076	0.266	0	1	47483432
Bronx dropoff	0.012	0.110	0	1	47483432
Brooklyn dropoff	0.082	0.275	0	1	47483432
Staten Island dropoff	0.000	0.014	0	1	47483432

Note: Trip duration is calculated as the difference between the pick-up time and the drop-off time. Unreasonable trips from the raw data are dropped using the following filters: trips with any negative cost components (cost components include base fare, extra fee, MTA tax, tip, tolls, improvement fee), trips with negative distance, trips with negative duration, trips greater than 200 miles, trips longer than 180 minutes. In total, less than 0.5% of the raw sample are dropped by these filters.

Table 7: Uber and Lyft Trips Records from Field Collection

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**
Trip duration (minutes)	17.847	9.625	2.817	107.316	75704
Trip distance (miles)	4.177	3.846	0.2	29.5	75704
Total fare ($)	21.479	15.336	3	209.8	75704
Manhattan pickup	0.766	0.423	0	1	75704
Queens pickup	0.118	0.323	0	1	75704
Bronx pickup	0.011	0.108	0	1	75704
Brooklyn pickup	0.102	0.303	0	1	75704
Manhattan dropoff	0.718	0.449	0	1	75704
Queens dropoff	0.115	0.319	0	1	75704
Bronx dropoff	0.025	0.157	0	1	75704
Brooklyn dropoff	0.140	0.347	0	1	75704
UberX	0.577	0.493	0	1	75704
UberXL	0.002	0.046	0	1	75704
UberBlack	0.157	0.364	0	1	75704
UberSUV	0.045	0.208	0	1	75704
UberPool	0.100	0.300	0	1	75704
Lyft	0.104	0.306	0	1	75704
LyftLine	0.011	0.106	0	1	75704
LyftPlus	0.001	0.033	0	1	75704

Note: This table summarizes the field data collection of 75,704 historical trip records from 443 Uber/Lyft drivers in NYC. We discuss the sampling methods and randomness of the data in the data appendix A.3.

Table 8: Description of the Sample

Variable	Mean	Std. Dev.	Min	Max	N
Pickup Count					
Taxi	4.835	8.800	1	410	6288102
UberX	0.906	1.078	0	24.345	6281657
UberXL	0.003	0.009	0	0.228	6280716
UberBlack	0.316	0.697	0	19.351	6280041
UberSUV	0.086	0.139	0	3.51	6262633
UberPool	0.184	0.264	0	5.84	6182534
Lyft	0.207	0.344	0	10.079	5893070
LyftLine	0.026	0.044	0	1.137	5876900
LyftPlus	0.003	0.009	0	2.483	5887722
Price per Service Minute ($)					
Taxi	1.153	0.117	0.695	5.199	6288102
UberX	1.111	0.286	0.538	5.75	6281657
UberXL	1.683	0.431	0.792	8.731	6280716
UberBlack	2.195	0.445	1.128	10	6280041
UberSUV	3.071	0.674	1.527	16.667	6262633
UberPool	0.964	0.257	0.124	5.833	6182534
Lyft	1.222	0.373	0.391	6.678	5893070
LyftLine	1.108	0.452	0.198	7.655	5876900
LyftPlus	1.864	0.567	0.588	10.296	5887722
Wait Time (minutes)					
UberX	4.012	2.671	1	30	6281657
UberXL	7.827	6.518	1	30	6280716
UberBlack	4.398	2.898	1	30	6280041
UberSUV	7.478	8.118	1	30	6262633
UberPool	4.338	3.277	1	30	6182534
Lyft	3.102	1.777	1	30	5893070
LyftLine	2.969	1.681	1	30	5876900
LyftPlus	4.582	2.376	1	30	5887722
UberTaxi	4.946	2.715	1	19.698	6288102
Route Characteristics (dummies)					
Rain	0.044	0.205	0	1	6288102
From airport	0.058	0.233	0	1	6288102
To airport	0.072	0.259	0	1	6288102
Morning rush	0.085	0.279	0	1	6288102
Evening rush	0.133	0.34	0	1	6288102
Weekday night	0.127	0.333	0	1	6288102
Weekday late night	0.158	0.365	0	1	6288102
Weekday day time	0.174	0.38	0	1	6288102
Weekend late night	0.066	0.249	0	1	6288102
Weekend day time	0.137	0.344	0	1	6288102
Friday and weekend night	0.119	0.324	0	1	6288102
Manhattan core	0.588	0.492	0	1	6288102
Lower Manhattan(LM)$^{\triangle}$	0.180	0.384	0	1	6288102
Midtown$^{\triangle}$	0.264	0.441	0	1	6288102
Uppereast and Upperwest(UE&UW)$^{\triangle}$	0.144	0.351	0	1	6288102
Non Manhattan core(NMC)	0.412	0.492	0	1	6288102

Note: This table provides a description of the sample at the pickupzone-dropoffpuma-month-day-hour-15min (jkt) level. The sample size 6,288,102 represents the number of jkt's, each of which has at least one taxi pickup. The variations in N is due to missing data of ride-sharing services in certain jkt's. The time blocks are defined as: morning rush (weekdays 7am-9am), evening rush (weekdays 4pm-7pm), weekday daytime (weekdays 10am-3pm), weekday night (weekdays 8pm-11pm), weekday late night (weekdays0am-6am), weekend day time (weekends 5am-5pm), weekend night (Friday 8pm-11pm and weekends6pm-11pm), and weekend late night (weekends 0am-4am).

$^{\triangle}$ Manhattan core is divided into 3 areas: Lower Manhattan, Midtown, Uppereast and Upperwest.

Table 9: Heterogeneous Consumer Taste

	Price/Time	LM	Midtown	UE & UW	NMC
Morning rush	α	0.199***	0.058*	0.136***	0.242***
		(0.044)	(0.031)	(0.016)	(0.023)
	β	0.554***	0.655***	0.479***	0.501***
		(0.091)	(0.090)	(0.046)	(0.080)
Evening rush	α	0.026**	0.094***	0.127***	0.099***
		(0.012)	(0.016)	(0.013)	(0.020)
	β	0.807***	0.676***	0.487***	0.644***
		(0.053)	(0.038)	(0.042)	(0.083)
Weekday night	α	0.124***	0.168***	0.335***	0.233***
		(0.011)	(0.018)	(0.041)	(0.016)
	β	0.570***	0.512***	-0.173	0.320***
		(0.037)	(0.031)	(0.127)	(0.077)
Weekday late night	α	0.170***	0.149***	0.457***	0.094***
		(0.019)	(0.015)	(0.141)	(0.021)
	β	0.421***	0.447***	-0.642	0.840***
		(0.067)	(0.050)	(0.544)	(0.095)
Weekday day time	α	0.113***	0.062***	0.266***	0.210***
		(0.012)	(0.012)	(0.018)	(0.014)
	β	0.663***	0.830***	0.102	0.561***
		(0.058)	(0.064)	(0.074)	(0.117)
Weekend night	α	0.209***	0.274***	0.294***	0.210***
		(0.019)	(0.025)	(0.022)	(0.009)
	β	0.272***	0.115**	-0.014	0.471***
		(0.046)	(0.054)	(0.057)	(0.046)
Weekend late night	α	0.180***	0.137***	0.383***	0.237***
		(0.011)	(0.014)	(0.043)	(0.010)
	β	0.587***	0.551***	-0.484***	0.519***
		(0.044)	(0.032)	(0.152)	(0.059)
Weekend day time	α	0.173***	0.135***	0.176***	0.222***
		(0.018)	(0.014)	(0.013)	(0.015)
	β	0.442***	0.533***	0.458***	0.512***
		(0.054)	(0.056)	(0.071)	(0.069)
Airport	α	-0.080***			
		(0.013)			
	β	0.668***			
		(0.128)			
Rain	β	0.474***			
		(0.027)			
Luxury (per service minute)		-0.104***			
		(0.009)			
Capacity (per service minute)		-0.110***			
		(0.010)			
N		14,464,715			

Note: This table presents the demand estimation results. Throughout the table, α indicates a row of price sensitivity estimates and β indicates a row of time sensitivity estimates. "Airport" is a dummy for to-airport trips. The time blocks are defined as: morning rush (weekdays 7am-9am), evening rush (weekdays 4pm-7pm), weekday daytime (weekdays 10am-3pm), weekday night (weekdays 8pm-11pm), weekday late night (weekdays0am-6am), weekend day time (weekends 5am-5pm), weekend night (Friday 8pm-11pm and weekends6pm-11pm), and weekend late night (weekends 0am-4am).
Standard errors are in parentheses. * represents statistical significance at 10% level, ** 5%, and *** 1%.

Table 10: Conterfactual Consumer Surplus Due to Entry of Ride-sharing (RS) Platforms (Unit: Dollar)

	Benchmark	**Taxi App**
Consumer Surplus of RS Users		
Per dollar spent on RS platforms	0.72	0.46
Per RS trip	14.05	8.86
Per RS service minute	0.92	0.58
RS Welfare Channels		
Time	56.4%	44.7%
Price	8.3%	12.4%
Luxury	18.8%	26.5%
Capacity	3.5%	4.9%
Comfort	13.0%	11.4%
Per-dollar Consumer Surplus of RS users: Heterogeneity		
UberX	0.88	0.48
UberXL	0.08	0.00
UberBlack	0.60	0.49
UberSUV	0.48	0.40
UberPool	0.20	0.03
Lyft	0.99	0.61
LyftLine	0.35	0.05
LyftPlus	0.61	0.08
Manhattan pick-up	0.64	0.51
Queens pick-up	1.44	0.20
Bronx pick-up	1.14	0.34
Brooklyn pick-up	1.16	0.12
Rush hours (morning rush and evening rush)	1.59	0.99
Non rush hours	0.37	0.24
Consumer Surplus of Taxi Users		
Per dollar spent on taxis	0.16	NA

Note: This table presents the counterfactual consumer surplus calculations. "Benchmark" stands for the benchmark counterfactual, and "Taxi App" stands for the second counterfactual in the paper where taxis adopt the same matching technology as ride-sharing platforms.

A Data Appendix

A.1 Calculation of Trip Cost P_{sjkt}

As mentioned in the main text, surge multiples and wait time are queried for all 263 zones approximately every minute, for all ride-sharing service types. Due to API query limit, we cannot query data on trip distance, duration, and cost for all 263x263 routes at 1-minute level. Instead, we query these variables for a route that begins in a given pick-up zone and ends in a randomly-chosen drop-off zone in a given minute. Due to this random assignment, any given route is expected to be queried approximately every 4 hours (4 hours*60 minutes per hour = 240 minutes). In particular, the 4-hour periods for a typical day are midnight - 4.00 a.m., 4:00 a.m. - 8:00 a.m., 8:00 a.m. - 12:00 p.m., 12:00 p.m. - 4:00 p.m., 4:00 p.m. - 8:00 p.m., 8:00 p.m. - midnight. We then use the trip distance and duration estimate in the 4-hour interval to proxy the minute-level trip distance and duration, for the same route.

The inputs for calculating P_{sjkt}, the type-route-minute level trip cost, now include surge multiple at $sjkt$, as well as trip distance and duration at $sjkt$ (proxied by the random draw in the 4-hour window). The only missing ingredient is how trip distance and duration map into the base price. One alternative method is a direct application of pricing formulas published by Uber and Lyft. However, trip-specific fees of various sorts are not observed by us, which likely causes a downward bias in trip cost estimate. We instead exploit the empirical relationship between trip distance/duration and trip cost by estimating the following equation separately for each service type:

$$\frac{\text{Trip Cost}_{jk\tilde{t}}}{\text{Surge Multiple}_{j\tilde{t}}} = \omega_0^s + \omega_1^s \text{Trip Distance}_{jk\tilde{t}} + \omega_2^s \text{Trip Duration}_{jk\tilde{t}} + \epsilon \tag{17}$$

where $\tilde{t}$ denotes the particular minute when information of the route jk is queried. Base price is calculated by dividing trip cost estimate at $jk\tilde{t}$ by the surge multiple at $jk\tilde{t}$. These parameter estimates ($\hat{\omega}_0^s$, $\hat{\omega}_1^s$, $\hat{\omega}_2^s$) then constitute an empirical mapping from trip distance and duration to trip cost P_{sjkt}, which is given by:

$$P_{sjkt} = \text{Surge Multiple}_{sjt}(\hat{\omega}_0^s + \hat{\omega}_1^s \text{Trip Distance}_{sjk\tilde{t}} + \hat{\omega}_2^s \text{Trip Duration}_{sjk\tilde{t}}) \tag{18}$$

A.2 Identifying Uber and Lyft Trips from TLC FHV Trip Records Data

The FHV trip data does not specifically indicate the company name of each trip, instead it shows the trip's dispatching base number. Using the official TLC list of FHV bases [34], we are able to identify Uber and Lyft trips by the correspondence between base numbers and company names. Specifically, the base numbers associated with Uber are B02512, B02395, B02617, B02682, B02764, B02765, B02835, B02836, B02864, B02865, B02866, B02867, B02869, B02870, B02871, B02872, B02875, B02876, B02877, B02878, B02879, B02880, B02882, B02883, B02884, B02887, B02888, and B02889. The base numbers associated with Lyft are B02510 and B02844.

A.3 Field Collection of Uber and Lyft Trip Records

We conducted two rounds of field surveys of Uber and Lyft drivers. The first round took place in January 2017 and the second route took place in March 2017. In both rounds, we requested for drivers' historical trip records from June to August 2016 so that all of our data sources are from the same time period.

We employed two sampling strategies in the data collection: a random sample and a convenience sample. In the collection of the random sample, the research team split into 4 groups, where two groups started around 9am at 2 locations in Manhattan, and the other two groups started at 2 locations in Brooklyn. Each group requested a trip to a randomly-selected borough out of Manhattan, Bronx, Brooklyn, and Queens. Upon arrival and before the driver answered a subsequent trip, the group made request to the driver for voluntary data disclosure. If the request was declined, they then offered a small sum of money in exchange for the data. The group collected as many trips as possible when the driver willingly accepted the request, either voluntarily or with a small sum of money, and the group chose to walk away when the monetary offer was rejected. The group repeated the same process throughout the day untill 9pm. In total, the research team collected 10,333 trips from 56 drivers out of 76 attempted.

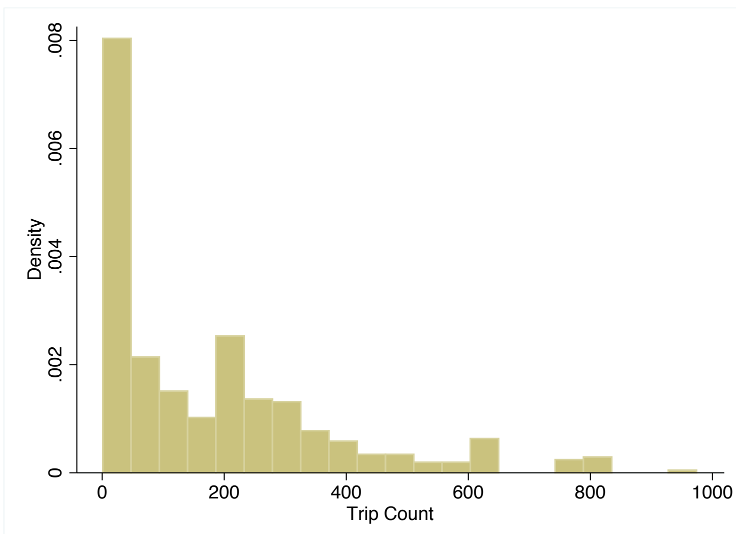
For the convenience sample, we approached Uber and Lyft drivers at places where they either were taking a break and/or were between trips. These places include restaurants, coffee shops, street corners, and parking lots. We followed the same data request procedure as for the random sample. Because we had more time interacting with drivers and recording data this way, the convenience sample is multiple times as large as the random sample. Table A1 compares these two

[34] See http://www.nyc.gov/html/tlc/downloads/pdf/find_a_ride.pdf

samples on various margins and demonstrates that the convenience sample is highly in line with the random sample.

The number of trips collected from a given driver varies greatly across drivers. As shown in Figure A1, a large share of trip records came from a small number of drivers while many drivers only gave a few trip records. Several factors may have contributed to this right-skewed distribution, such as the sampling approach, heterogeneous driver tastes of privacy, driver tenure, etc. To check on selection, we split the sample into trips collected from large drivers ($\geq$ 300 trips) and trips collected from small drivers ($<$ 300 trips), and then compare these subsamples with the random sample. Table A1 shows that these subsamples are overall consistent with the random sample and selection on driver size (in terms of trips collected) appears to be insignificant.

Figure A1: Trips Collected Vary across Drivers



A.4 Inference of D_{sjkt}

Due to the data limitation of Uber and Lyft trips published by TLC, the finest level one can get is D_{jt}^{Uber} and D_{jt}^{Lyft}, where D_{jt}^{Uber} measures the total trip counts of all 5 service types on Uber at the pick-up location j in time t, and D_{jt}^{Lyft} is the total trip counts of all 3 service types on Lyft at the pick-up location j in time t. To infer trip counts at a finer $sjkt$ (type-pickup-dropoff-time) level, we exploit the field-collected sample of 75,704 Uber and Lyft trip records using the following procedure:

Step 1: Construct a vector of zeroes, whose length is $s \times j \times k \times t$, i.e., at the type-month-day-time-hour-15min level. Fill any $sjkt$ cell with 1, if a trip is observed in that particular cell from

Table A1: Comparison Between Various Sub-samples from Field Collection

	Random Sample	**Convenience Sample**	**Large Drivers**	**Small Drivers**
N	10333	65371	37307	38397
Pick-up Location				
LM	0.202	0.203	0.184	0.221
	(0.401)	(0.402)	(0.387)	(0.415)
Midtown	0.349	0.328	0.270	0.390
	(0.477)	(0.470)	(0.444)	(0.488)
UE&UW	0.168	0.165	0.171	0.160
	(0.374)	(0.371)	(0.377)	(0.367)
NMC	0.281	0.303	0.375	0.228
	(0.450)	(0.460)	(0.484)	(0.420)
Drop-off Location				
LM	0.192	0.184	0.172	0.197
	(0.394)	(0.387)	(0.377)	(0.398)
Midtown	0.305	0.291	0.239	0.345
	(0.46)	(0.454)	(0.426)	(0.475)
UE&UW	0.169	0.160	0.162	0.162
	(0.375)	(0.367)	(0.368)	(0.368)
NMC	0.335	0.365	0.428	0.296
	(0.472)	(0.482)	(0.495)	(0.457)
Pick-up Time				
Morning rush	0.123	0.096	0.086	0.113
	(0.329)	(0.295)	(0.28)	(0.317)
Evening rush	0.126	0.152	0.175	0.123
	(0.332)	(0.359)	(0.38)	(0.328)
Weekday night	0.119	0.151	0.172	0.122
	(0.323)	(0.358)	(0.377)	(0.327)
Weekday late night	0.093	0.131	0.064	0.186
	(0.29)	(0.338)	(0.244)	(0.389)
Weekday day time	0.268	0.180	0.190	0.193
	(0.443)	(0.384)	(0.392)	(0.395)
Weekend late night	0.042	0.057	0.029	0.08
	(0.201)	(0.232)	(0.168)	(0.271)
Weekend day time	0.141	0.117	0.137	0.105
	(0.348)	(0.321)	(0.343)	(0.306)
Weekend night	0.088	0.117	0.148	0.079
	(0.283)	(0.321)	(0.355)	(0.269)
Trip Distance				
$\leq$ 2 miles	0.338	0.336	0.262	0.409
	(0.473)	(0.472)	(0.440)	(0.492)
$>$2 miles and $\leq$5 miles	0.416	0.404	0.437	0.376
	(0.493)	(0.491)	(0.496)	(0.484)
$>$5 miles	0.246	0.259	0.301	0.215
	(0.431)	(0.438)	(0.459)	(0.411)
Trip Duration				
$\leq$ 10 minutes	0.162	0.168	0.108	0.226
	(0.368)	(0.374)	(0.31)	(0.418)
$>$ 10 minutes and $\leq$ 20 minutes	0.550	0.541	0.535	0.549
	(0.497)	(0.498)	(0.499)	(0.498)
$>$ 20 minutes	0.288	0.291	0.357	0.226
	(0.453)	(0.454)	(0.479)	(0.418)

Table A1: Comparison Between Various Sub-samples from Field Collection (Continued)

	Random Sample	Convenience Sample	Large Drivers	Small Drivers
N	10333	65371	37307	38397
Service Type				
UberX	0.566	0.579	0.817	0.344
	(0.496)	(0.494)	(0.386)	(0.475)
UberXL	0.002	0.002	0.000	0.004
	(0.047)	(0.046)	(0.014)	(0.063)
UberBlack	0.170	0.155	0.029	0.282
	(0.376)	(0.362)	(0.169)	(0.45)
UberSUV	0.051	0.045	0.010	0.080
	(0.219)	(0.207)	(0.098)	(0.272)
UberPool	0.095	0.101	0.143	0.059
	(0.293)	(0.302)	(0.35)	(0.236)
Lyft	0.103	0.105	0.000	0.206
	(0.304)	(0.306)	(0.019)	(0.404)
LyftLine	0.012	0.011	0.000	0.023
	(0.111)	(0.106)	(0.000)	(0.148)
LyftPlus	0.001	0.001	0.000	0.002
	(0.024)	(0.035)	(0.016)	(0.045)
Pick-up Location x Drop-off Location				
LM - LM	0.066	0.067	0.049	0.084
	(0.249)	(0.259)	(0.216)	(0.278)
LM - Midtown	0.078	0.072	0.067	0.08
	(0.269)	(0.259)	(0.25)	(0.271)
LM - UE&UW	0.021	0.029	0.022	0.018
	(0.144)	(0.139)	(0.146)	(0.132)
LM - NMC	0.036	0.044	0.046	0.040
	(0.186)	(0.204)	(0.209)	(0.195)
Midtown - LM	0.081	0.073	0.069	0.079
	(0.272)	(0.260)	(0.253)	(0.270)
Midtown - Midtown	0.131	0.126	0.075	0.177
	(0.338)	(0.332)	(0.263)	(0.382)
Midtown - UE&UW	0.065	0.060	0.053	0.067
	(0.247)	(0.237)	(0.225)	(0.25)
Midtown - NMC	0.072	0.070	0.073	0.066
	(0.258)	(0.254)	(0.261)	(0.249)
UE&UW - LM	0.019	0.020	0.024	0.016
	(0.137)	(0.140)	(0.153)	(0.124)
UE&UW - Midtown	0.060	0.055	0.053	0.058
	(0.237)	(0.227)	(0.223)	(0.234)
UE&UW - UE&UW	0.051	0.050	0.044	0.055
	(0.219)	(0.217)	(0.205)	(0.229)
UE&UW - NMC	0.038	0.041	0.051	0.031
	(0.191)	(0.198)	(0.219)	(0.173)
NMC - LM	0.025	0.024	0.03	0.018
	(0.157)	(0.152)	(0.17)	(0.133)
NMC - Midtown	0.035	0.037	0.044	0.030
	(0.185)	(0.189)	(0.206)	(0.17)
NMC - UE&UW	0.032	0.032	0.042	0.021
	(0.175)	(0.175)	(0.202)	(0.144)
NMC -NMC	0.189	0.211	0.258	0.159
	(0.392)	(0.408)	(0.438)	(0.366)

the field-collected sample. [35] Then the vector contains 0's and 1's.

Step 2: Estimate a probit model of the vector in Step 1 to predict the probability of a trip in $sjkt$ by a number of location-time fixed effects:

$$
\begin{aligned}
Pr(1 \text{ trip in } sjkt) = & f(\text{pickup zone}, \text{ dropoff puma}, \text{ service type}, \text{ pickup hour}, \\
& \text{pickup borough} \times \text{ pickup hour}, \text{ pickup borough} \times \text{ dropoff puma}, \\
& \text{pickup borough} \times \text{ service type}, \text{ dropoff puma} \times \text{ service type})
\end{aligned}
$$

Step 3: Calculate D_{sjkt} by distributing D_{jt}^{Uber} and D_{jt}^{Lyft} into service types and drop-off locations. This requires constructing weights using the estimated p_{sjkt} in Step 2, and applying the following formulas (Note that s = 1, 2, 3, 4, 5, for 5 service types on Uber, and s = 6, 7, 8, for 3 service types on Lyft):

For Uber:

$$D_{sjkt} = \frac{p_{sjkt}}{\sum_{k=1}^{263} \sum_{s=1}^{5} p_{sjkt}} D_{jt}^{Uber}$$

For Lyft:

$$D_{sjkt} = \frac{p_{sjkt}}{\sum_{k=1}^{263} \sum_{s=6}^{8} p_{sjkt}} D_{jt}^{Lyft}$$

These weights ensure that the inferred D_{sjkt}'s return the value of D_{jt}^{Uber} and D_{jt}^{Lyft}, when summed over service types and drop-off locations.

[35] In several rare cases we observe two trips within the same $sjkt$ cell. In these cases, we randomly drop one of the two trips.