Study of Demand in Taxi Market
The Case of New York City

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Declaration

I, Takahiro Matsumoto, hereby declare that the work presented in this dissertation is my own original work. Where information has been derived from other sources, I confirm that this has been clearly and fully identified and acknowledged. No part of this dissertation contains material previously submitted to the examiners of this or any other university, or any material previously submitted for any other assessment.

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Classification

This piece of research is primarily:

☑ an empirical/econometric study

☐ the examination of a theoretical problem

☐ a critical analysis of a policy issue

☐ an analytical survey of empirical and/or theoretical literature

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Abstract

In this paper, I study the properties of the demand curve of the taxi market in New York City with rich trip data of yellow cabs and ride-hailing services. As the pricing scheme is determined by the authority in the taxi market and thus price does not vary depending on market conditions, I construct a model connecting unobservable waiting passengers and wait time, which would be a part of market clearing variables. Taking advantage of price increase in 2012, I estimate elasticities of demand with respect to price and wait time and have found that they are both inelastic and independent of trip distances. In addition, the elasticity of demand for yellow cabs with respect to wait time after Uber became popular is higher, implying that yellow cabs and ride-hailing services are substitutes each other to some extent. Lastly, welfare analysis suggests that Uber and other ride-hailing services have dramatically increased the total consumer surplus by door-to-door transportation.

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Contents

1 Introduction **1**

2 Related Literature **2**

3 Description of the Markets and Data **4**

3.1 Industrial Characteristics 4

3.1.1 Taxi Market 4

3.1.2 Ride-Hailing Market 6

3.2 Data and Descriptive Evidence 7

3.2.1 Data 7

3.2.2 Summary of TLC Data 7

3.2.3 Taxi Fare Increase in September 2012 10

3.2.4 Uber's Fare Cut 11

4 Model and Estimation **12**

4.1 Model Construction 12

4.1.1 Wait Time and Waiting Passengers 12

4.1.2 Demand Curve 14

4.2 Estimation 15

4.2.1 Properties of Data and Model 15

4.2.2 Demand Curve Estimation 18

4.3 Welfare Analysis of Price Increase 21

5 Analysis of Uber's Effects on Taxi Market **23**

5.1 Uber's Effects on Demand for Yellow Cabs 23

5.2 Welfare Analysis of Uber's Rise 26

6 Concluding Remarks **27**

References **29**

A Supply Side Analysis: Labor and Taxicabs **31**

B Locations and Road Length **32**

C Robustness Check **33**

D Auxiliary Tables **34**

List of Figures

Figure 1	Map of Service Area	5
Figure 2	Daily Trips (2013-2016)	8
Figure 3	Distribution of Trips by Borough/District (Yellow Cabs)	8
Figure 4	Distribution of Trips by Borough/District (Boro Taxis)	9
Figure 5	Distribution of Trips by Borough/District (Uber)	9
Figure 6	Change in the Number of Trips (2011-2012 vs 2012-2013)	10
Figure 7	Schematic of Location i	13
Figure 8	Locations in Manhattan	16
Figure 9	Number of Pickups in Manhattan	17
Figure 10	Price Elasticities of Area-to-area Routes	21
Figure 11	Consumer Surplus by Trips from k to l	22
Figure 12	Estimate of Uber's Effect	27

List of Tables

Table 1 Fare Comparison 11
Table 2 Summary of the Variables Used in the Model 14
Table 3 Summary of the Statistics 18
Table 4 Elasticity of Demand w.r.t Own Price and Wait Time 19
Table 5 Elasticity of Demand w.r.t Own Price with Cross Terms 20
Table 6 Comparison of Surplus 23
Table 7 Elasticity of Demand w.r.t Uber's Trips and Wait Time 25
Table 8 Elasticity of Demand w.r.t Uber's Trips with Cross Terms 26
Table 9 Elasticity of Demand w.r.t Wait Time for Each Pickup Area 28
Table 10 Daily Consumer Surplus by Yellow Cabs and Uber 28
Table 11 Locations and Road Length 32
Table 12 Elasticity of Demand w.r.t Own Price and Wait Time (N=7,000) . . . 33
Table 13 Elasticity of Demand w.r.t Own Price and Wait Time (N=9,000) . . . 33
Table 14 Elasticity of Demand w.r.t Uber's Trips and Wait Time (N=8,000) . . 34
Table 15 Elasticity of Demand w.r.t Uber's Trips and Wait Time (N=10,000) . 34
Table 16 Variance-Covariance Matrix of Table 5 35
Table 17 Elasticity of Demand w.r.t Own Price for Each Pickup/Dropoff Area . 36
Table 18 Elasticity of Demand w.r.t Wait Time with Cross Terms 37
Table 19 Variance-Covariance Matrix of Table 18 38

1 Introduction

This paper aims to study the properties of demand in taxi markets. I estimate the elasticities of demand for taxis with respect to price and wait time and analyze the effects of the increase in taxi fare on social welfare as well as how the rise of ride-hailing services have influenced taxi markets. The markets have many differences compared to other transportation sectors, and one of the most prominent aspects is that both passengers and drivers don't know where they are each other. Moreover, as the fare and the quantity of taxis are highly regulated by authorities in many taxi markets, price and quantity by themselves cannot smoothly vary to be market clearing variables like other markets. Rather, wait time for passengers and search time for drivers vary flexibly to equilibrate supply and demand in the taxi markets, at least in the short run. In this paper, I build a spatial model to surmise these variables from data of the taxi market in New York City (NYC) and then estimate the demand curve.

A challenge to building a demand model is that I don't observe passengers' wait time and also the number of waiting passengers, as the data are just results in equilibrium. Additionally, NYC Taxi and Limousine Commission (TLC), the authority of the market, stopped providing a panel identifier, namely driver's hack numbers and medallion IDs for each trip, due to concern about driver's privacy, so I don't know either each cab's search time or the number of searching cabs. However, as average search time can be calculated from the public data on hourly basis and there are some papers which identify drivers like Frechette et al.(2016 [1])[1], I handle supply side by fixing the number of working cabs constant conditional on hours and pickup locations with those data and evidence. Under the assumption, I extrapolate the relationship between unobservable wait time and waiting passengers with the observed equilibrium data, the number of searching cabs and so on. Then I estimate the effects of wait time and the fare increase on the number of waiting passengers with two stage least squares (2SLS).

Next, I estimate the effects of Uber's rise on taxi markets using the model specified above. As Uber grew rapidly during 2015 and 2016 but cut its standard fare in NYC by approximately 15 % in January 2016, it is difficult to tell the difference of the cause of the decrease in the number of trips by yellow cabs between Uber's price cut effects (cross price elasticity) and other reasons. I here assume that the decrease in the number of trips was due to Uber (or broadly, ride-hailing services) under control of wait time and other exogenous factors like weather. I overcome the problem by taking advantage of the existence of minimum fare. Namely, if the fare is smaller than the minimum, there was no price change before and

[1] They show that almost all of the yellow cabs are working at least once a day on weekdays and they are intensely used during peak time, for example.

after fare cut, while if it exceeds, the price decreased proportionately. Thereupon, if the number of trips by yellow cabs whose trip distance is long enough so that the minimum fare wouldn't have applied if passengers would have chosen Uber declined sharply than others, then the difference would be accrued to the price change.

I choose the market in NYC as a case study to learn the properties of the demand curve in taxi markets because the city discloses rich individual trip data completed by taxis and ride-hailing services. In addition, TLC increased the fare and thus made it possible to estimate own price elasticity of demand for yellow cabs. Furthermore, Uber cut its standard fare, so I can also study the cross price elasticity. These natural experiments are exploited to study the characteristics of the demand curve.

From the model and the data in the NYC taxi market, I find that the elasticities of demand for taxis with respect to both wait time and price are inelastic, price elasticities are overall independent of the distances of trips, and that the fare increase had a negative impact on the total social welfare. Additionally, I show that the wait time elasticity has become less inelastic after Uber became well-known, which indicates that it is partially recognized as the substitute to taxis, and that Uber's rise has expanded the total demand for door-to-door transportation and thus greatly increased the total consumer surplus.

The structure of this paper is as follows. Section 2 introduces the related literature of demand/supply models of taxi markets and Uber, especially the two main references on which my model is based. Section 3 looks over the taxi/ride-hailing markets in NYC, shows the TLC data, and analyzes the data to find some evidence of those markets. Section 4 builds the demand model by specifying the relationship between wait time and waiting passengers. Then I estimate the model with data, analyze the effects of the fare increase, measure consumer surplus, and discuss the results. Section 5 extends the estimation to see the Uber's effects on the taxi market in NYC. I conclude the study in Section 6.

2 Related Literature

The NYC taxi market has been studied by many papers, one of the most seminal and controversial papers being Camerer et al. (1997 [2]) regarding labor supply curve of taxi drivers. Analyzing trip sheets from NYC cab drivers, they conclude that the elasticity of labor supply with respect to wage is negative and insist that this might be due to daily income target and no intertemporally substituting labor and leisure across days[2], which

[2]They call the labor supply decision, "one day at a time" as in the paper title.

contradicts with the neoclassical theory. It provoked a lot of discussions and though some studies show the result consistent with the paper like Chou (2002 [3]) in the Singapore taxi market, Farber (2005 [4]) criticizes that the negative elasticity comes from econometrics issues and insists that it is not actually negative. He indicates that cab drivers' income effects are small and when to quit on a daily basis is highly dependent on cumulative daily hours to that point. In Farber (2015 [5]), he uses TLC data with hack/medallion numbers and shows that the elasticity is certainly positive.[3] In my model, I set the number of yellow cabs fixed conditional on locations and dates.

There are also some papers studying demand side or general equilibrium of taxi markets.[4] My demand model is mainly based on the two papers; Frechette et al. (2016) and Buchholz (2016 [10]), though their main interests lie in the inefficiency of regulations or search frictions in taxi markets, which are different from my purpose of this paper. I somewhat combine the essence of the models in the two papers in a simpler way to study effects of the fare increase of yellow cabs and the rise of ride-hailing services on demand for yellow cabs. Frechette et al. (2016) build demand equations with unobservable wait time and the number of waiting passengers for taxis, with TLC data from 2011 to 2012, taking advantage of the geographical characteristics of Manhattan and using traffic speed outside Manhattan as an instrument (supply shifter), and estimate that the elasticity of demand with respect to wait time is inelastic. I follow the strategy but incorporate spatial aspects in order to take price change into consideration. They also model the labor supply dynamics to study how the equilibrium is influenced by taxi regulations and also matching technologies, which I don't.

Buchholz (2016) studies the spatial equilibrium and search frictions of taxi markets in NYC. He focuses on fare variations depending on distance and estimates demand as a function of price. Importantly, his identification of demand and supply in the spatial equilibrium model crucially depends on fixed labor supply, which he justifies with the notion that medallion limits are binding during the busy time. This is the same strategy I apply in my demand model, though he explicitly admits vacant cabs moving to other locations to search for passengers. He also estimates the effect of the fare increase in 2012 on welfare and studies the value of improved matching technologies and differential pricing used by ride-hailing services, but does not analyze the influence of ride-hailing services on yellow cabs directly.

[3]The similar results were shown by using Uber data both in the intensive and extensive margin, though decision making by taxi drivers and Uber drivers might be very different. Chen and Sheldon (2016 [6]) apply discontinuity design to show the elasticity is positive and causal. Hall and Kruger (2016 [7]) study how Uber drivers operate their sessions with survey data and have found that only 6% of respondents have some income targets. Sheldon (2015 [8]) replicates the study of Camerer et al. (1997) with Uber data, finding the elasticity being still positive and statistically significant and indicating that measurement errors lead to highly negative elasticities in their paper.

[4]Lagos (2003 [9]) is a classical paper researching NYC taxi market with a dynamic equilibrium model.

Cohen et al. (2016 [11]) study own price elasticity with Uber data when the price is surged due to tight market conditions. When Uber increases the price, it multiplies standard fare by the surge multiplier shown to passengers. They estimate demand curve, using the property of continuous surge multiplier being rounded to discrete price increments when it is multiplied (e.g. the multiplier 1.249 rounded down to 1.2 times base fare, while 1.250 up to 1.3x), applying the econometric regression discontinuity analysis as well as the propensity score methods and conclude that demand is in most cases inelastic.

3 Description of the Markets and Data

3.1 Industrial Characteristics

3.1.1 Taxi Market

In NYC, yellow cabs are regulated by NYC Taxi and Limousine Commission (TLC). Each taxicab vehicle has to be equipped with a medallion, a small metal plate and license required to operate taxicabs in NYC and issued by TLC.[5] The authority controls the fare system, the (maximum) number of medallions and so on.[6] Street hail livery vehicles (as known as "boro taxis" or "green cabs") are another type of taxis also regulated by TLC. They have fare structure in common, but are different in that while yellow cabs can pick passengers up at any spot in 5 boroughs in NYC (Manhattan, Brooklyn, the Bronx, Queens, and Staten Island), boro taxis are prohibited to pick them up at Manhattan (excluding the northern districts) and the airports, John F. Kennedy and LaGuardia.[7] See the map in Figure 1.

The taxi market in NYC is large. According to Buchholz (2016), approximately 700 million passengers get on taxis in 2013 in the United States and NYC consists of as much as 34% of the number. In revenues, NYC generates about 4 billion dollars annually, which is 25 % of the whole U.S. market.

There are mainly two types of medallions. One is corporate medallion, so-called "mini-fleet", owned by corporations and can be leased out to individual drivers or the companies can hire employees to drive. They were requested to drive two shifts per day including weekends and holidays, and each shift had to be longer than 9 hours. The restriction was removed

[5] The word "(yellow) medallion" is often used to mean just yellow cabs. I follow this convention in this paper and use the both words interchangeably.

[6] See the classic paper, Schreider (1975 [12]) for theoretical reasons of those regulations.

[7] As boro taxis are the livery services, passengers can call the base for pre-arranged trips and also negotiate prices in that case. Only for pre-arranged trips can passengers get on boro taxis from airports.

in February 2015 for the sake of more flexibility.[8] The other type is owner-owned medallion. Some individual drivers own and drive medallions and can decide when and how much to work flexibly. There was once a regulation, known as owner-must-drive, that they had to drive at least 210 nine-hour shifts a year and if they violated, they had to pay fines. This restriction was also removed in February 2016.[9] These restrictions partially justify fixing the number of medallions conditional on locations and dates in my model. According to 2014 TLC Factbook, approximately 60% of medallions are minifleets and the rest is owner-operated ones and the Factbook (2016 version) shows that there are 13,587 yellow cabs (and 7,676 boro taxis) in NYC.[10] Medallions can be traded in the market. They were once sold for more than 1.3 million dollars in 2013 but plummeted to just 241,000 dollars in 2017, and the main reason would be the rise of ride-hailing services.[11]

Figure 1: Map of Service Area

Source: TLC

[8] http://www.nyc.gov/html/tlc/downloads/pdf/newly_passed_rule_drv_veh_owner_updated.pdf

[9] http://www.nyc.gov/html/tlc/downloads/pdf/proposed_rules_omd_repeal_2016.pdf

[10] These numbers, combined with evidence from Frechette et al.(2016), are used later to calculate the number of medallions in my model.

[11] http://nypost.com/2017/04/05/taxi-medallions-reach-lowest-value-of-21st-century/

3.1.2 Ride-Hailing Market

Ride-hailing services have become popular dramatically in 2010's, taking advantage of the development of information technology and the emergence of smartphones.[12] They were successful in mitigating the inefficiencies of taxis such as search frictions, illiquidity of prices and the fixed (maximum) number of vehicles. The market leader, Uber, has more than 70 % shares (2016, based on the number of trips) in NYC and operates globally, and it became so popular that the word "Uber" is now used as a verb or the phenomenon is referred to "Uberfication".[13] Cars used in the service are mainly privately owned by drivers and not for the commercial purpose originally. Drivers are also very flexible about when and how much to supply their labors. Candidate drivers in NYC attend 24-hour FHV class at TLC-approved school and take a defensive driving course to be drivers. The number of active drivers is growing rapidly and the number of weekly vehicles dispatched by Uber surpassed the number of yellow cabs in May 2015, and even Lyft, the second biggest U.S. ride-hailing service which has approximately 10% market share (2016) in NYC, also dispatched more vehicles than yellow cabs.[14] Note that while most taxi drivers work full time, drivers serving for ride-hailing markets are often part-timers, and many drivers work for both Uber and Lyft, so the number of dispatched vehicle somewhat overestimates the capacity of supply by ride-hailing services.

Those companies provide various types of ride-hailing services in NYC. I take Uber for example. The closest substitute to taxis is UberX, which is launched in September 2011 in NYC, driven by standard sedan and most popular[15]. As written later, Uber cut its fare in January 2016 and became cheaper than taxis on average. According to Cohen et al. (2016), UberX represents approximately 80% of all service by Uber, and thus when I refer to Uber or ride-hailing services in this paper, UberX or its equivalent is in mind. Some premium car services like UberBlack are also provided. There is also a service of sharing of ride-sharing, UberPOOL, where passengers who head for the same direction with near pickup/dropoff locations are matched. It started from January 2015 in NYC, with lower fare than UberX. Uber has an algorithm to increase the price when demand is high, so-called "surge pricing" whose detail is not disclosed.[16] The algorithm makes it possible to efficiently dispatch cars to

[12]Ride-hailing markets, sometimes called ride-sharing markets, are considered as an industry of sharing economy or "gig" economy, whose essence is that there are underutilized goods (cars) owned by some individuals, and both owners and non-owners benefit from consuming those goods together via transferring rents. The ride-hailing service is unique in that car owners also provide their labors.

[13]There is still plenty of room to expand dramatically. Lashinsky (2017 [13]) discloses that though about half of Americans have ever heard of ride-hailing, just 15% have an experience of the service.

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

[15]There are also services by van for higher capacity called UberXL whose fare is slightly higher.

[16]Chen et al. (2015 [14]) partially disclose how it works by creating dummy accounts and using public

waiting passengers and to raise fare when the market is tight so that only passengers with high valuation request cars and drivers are incentivized.[17] Lyft and other ride-hailing companies also provide similar services, though some don't apply price alternation mechanism.

3.2 Data and Descriptive Evidence

3.2.1 Data

Data I use in this paper are mainly based on Taxicab & Livery Passenger Enhancement Programs (TPEP/LPEP) data disclosed by TLC, which include all individual trips by yellow cabs since 2009, boro taxis (green cabs) since its launch in August 2013, and For-Hire Vehicle (FHV) including Uber and Lyft since 2015.[18] For yellow cabs and boro taxis, each trip data has pickup and dropoff time, trip distance, pickup/dropoff longitude and latitude[19], pricing scheme (standard, John F. Kennedy Airport, etc.), payment method (cash or card), fare amounts, surcharges/tolls, tips amount (only when paid by credit card) and so on. Unfortunately, there is no data who the drivers were or which cabs were used for each trip (such as hack number or medallion IDs), so I don't know each driver's supply, let alone when and how long they were searching for potential passengers. With respect to FHV, the available data are limited and only contain dispatcher ID (no driver identified, but able to distinguish Uber from other Limo services, for example), pickup time and location ID showing rough location almost the same as in Figure 8 in the next section.

3.2.2 Summary of TLC Data

The number of average daily trips in the whole New York City from 2013 to 2016 is summarized in Figure 2. Though not shown in the figure, trips by yellow cabs from 2009 and 2012 are very similar with those of 2013. Limo and Black car services are excluded. Since TLC doesn't have trip data of FHV before 2015, these numbers are just set to be 0. Though there were certainly some trips completed by ride-hailing services during the period, various evidence implies that the number is almost negligible compared to that by taxis.[20] As

Uber API, and show their concerns about its fairness and transparency.

[17]Cramer and Kruger (2016 [15]) compare the efficiency of taxis with that of ride-hailing services with respect to capacity utilization rate in five cities in the U.S. and conclude that it is much higher for Uber drivers than taxi drivers in most cities. Interestingly, the only exception is NYC, where the utilization rate is almost identical between taxis and Uber. This would be because highly densely populated NYC makes efficient matching possible.

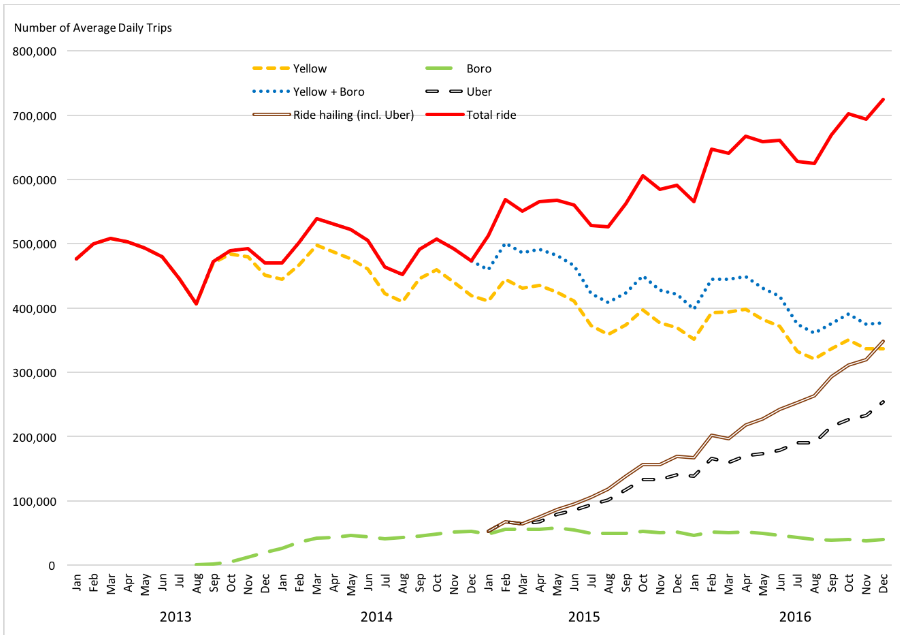
[18]http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml

[19]Since July 2016, these are replaced by location ID in the same way as FHV.

[20]For example, see http://toddwschneider.com/posts/analyzing-1-1-billion-nyc-taxi-and-uber-trips-with-a-vengeance/

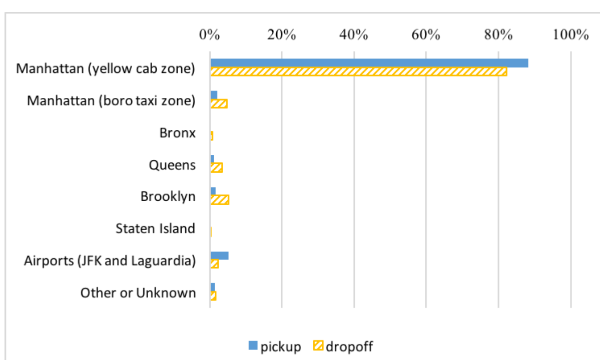
expected, the number of trips by yellow cabs have declined in these days, while the number of trips by ride-hailing companies has grown at a significant pace[21], and the total demand for taxi-like transportation actually has increased from approximately 500,000 to 700,000.

Figure 2: Daily Trips (2013-2016)



The following Figures 3 to 5 show the distribution of trips which started/ended at each borough/district by yellow cabs, boro taxis, and Uber in July 2016. As TLC has no data of dropoff locations of trips by Uber, only distribution by pickup locations is in the chart. Other or unknown districts include New Jersey/ New Ark airport.[22]

Figure 3: Distribution of Trips by Borough/District (Yellow Cabs)



[21]This is the sum of the trips by Uber, Lyft, Via, Gett, and Juno.

[22]Passengers can get on yellow cabs only at New Ark airport in New Jersey. Yellow cab drivers are not authorized to pick passengers up on the road in New Jersey. http://frlimo0.tripod.com/njtaxiregulations.htm

Figure 4: Distribution of Trips by Borough/District (Boro Taxis)

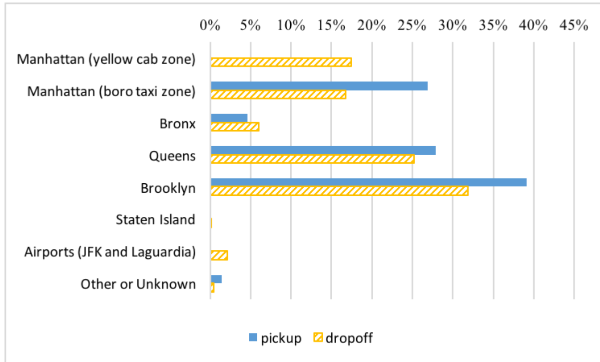
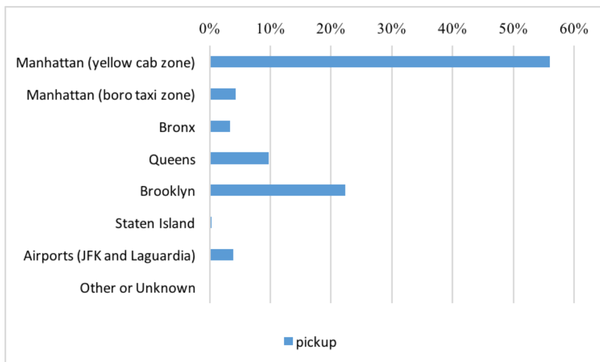


Figure 5: Distribution of Trips by Borough/District (Uber)



As the figure indicates, more than 80 % of trips by yellow cabs started or ended within yellow cab zones. Dropoff districts are relatively distributed. Regarding boro taxis, they can't be hailed within yellow cab zone in Manhattan and airports[23], but they sometimes drop off in those areas. More than half of the trips started or ended outside Manhattan.

Though Uber drivers pick passengers up mainly in Manhattan, the percentage of pickups in outer boroughs, especially in Brooklyn, is higher than that by yellow cabs. This might be due to the situation that 1) passengers have to wait for yellow/green cabs for longer time in outer boroughs and thus Uber becomes more convenient and 2) they often take longer trips and therefore Uber is much cheaper than taxis.[24]

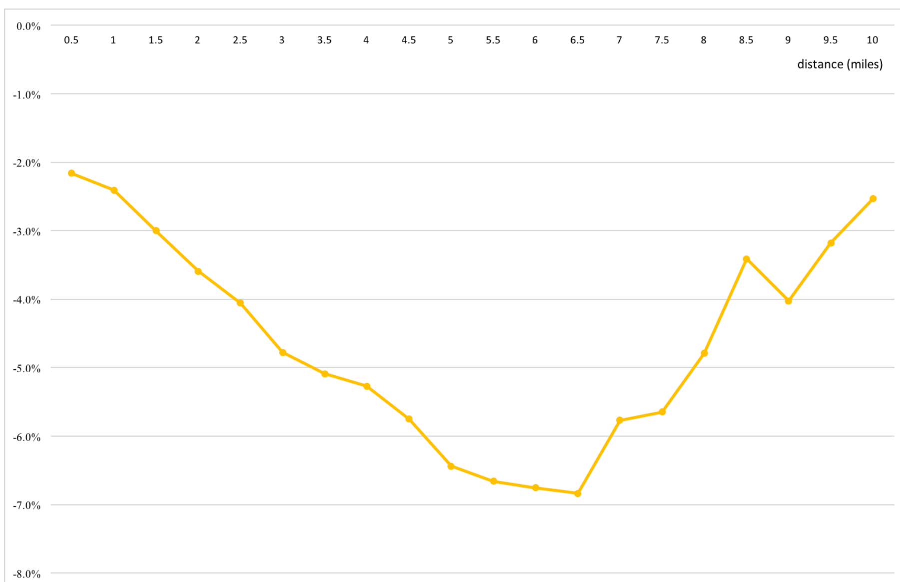
[23]There are some pickups by boro taxis at airports. This would be pre-arranged trips which are allowed as they are livery services.

[24]See 3.2.4.

3.2.3 Taxi Fare Increase in September 2012

TLC raised the fare from 40 cents to 50 cents per 1/5 mile (or per 60 seconds when the traffic is slower than 12 mph) in September 2012. Base fare (first 1/5 mile) remained the same; 2.5 dollars.[25] Figure 6 shows how the number of trips in NYC changed before and after fare increase monthly, based on the different trips' distance. The horizontal axis is the distance in miles. Since the base fare was unchanged, the percentage of the fare increase is higher for longer trips. As the figure indicates, compared to the number of trips between September and July from 2011 to 2012, the equivalent number during the same period from 2012 to 2013 decreased by approximately 3.5% on average, and this is not due to Uber.[26] Actually, it is possible that supply increased (and hence expected wait time decreased) so that I underestimate the demand decrease.

Figure 6: Change in the Number of Trips (2011-2012 vs 2012-2013)



As seen in Figure 2, the number of trips by yellow cabs started to significantly decline from 2014, but it would be natural to consider that the causes are mainly the introduction of boro taxis and rise of Uber. This might suggest that taxis and other public transportations are not so close substitute, while taxis and Uber are very close. I will see how demand changed by fare increase in the next section.

[25]This is standard fare system, which consists of most trips by yellow cabs. A typical exception is a trip between Manhattan and JFK airport. The rate is flat and rose from \$45 to \$52 by the fare increase.

[26]I eliminated August because boro taxis were introduced in August 2013.

3.2.4 Uber's Fare Cut

Uber cut its fare by approximately 15% at the end of January 2016 and announced that the fare on average became lower than that of taxi's.[27]. The following table[28] summarizes how fare changed before and after Uber's fare cut (and also yellow cab's fare increase).

Table 1: Fare Comparison

	Yellow Cab		Uber	
($)	~ 2012 Aug	2012 Sep ~	~ 2015 Dec	2016 Jan ~
Base Fare	2.5		3.0	2.55
Per 1/5 mile	0.4	0.5	0.43	0.35
Per minute	0.4	0.5	0.4	0.35
Minimum Fare	-	-	8.0	7.0
Permanent Surcharge	0.5	0.8*	"Surge Pricing" depending on market conditions	
Night (8pm-6am)	1.0	1.0		
Weekday (4pm-8pm)	0.5	0.5		

*Permanent surcharge rose to $0.8 in January 2015.

As at least $0.8 surcharge is imposed on every taxi trip[29], base fare is virtually higher for taxis and per-1/5-mile fare[30] is also higher for yellow cabs before and after Uber's fare cut, so whether Uber fare is higher or not depends on if the taxi fare is lower than Uber's minimum fare or not, except when the Uber's surge pricing is working.[31] If tips are not considered, which is almost mandatory for yellow cabs but discouraged for Uber trips[32], the threshold in miles where Uber becomes cheaper is around 1.8 miles depending on days or time due to miscellaneous surcharges. In addition, whether fare of Uber trips actually decreased or not depends on distance; if it is longer than about 2.5 miles after fare cut, the fare actually decreased.[33]

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[27]https://newsroom.uber.com/us-new-york/lower-prices-increased-demand/

[28]Fare on the table is that of UberX. I hereafter assume that all of the Uber trips were operated by UberX.

[29]For detailed information, see http://www.nyc.gov/html/tlc/html/passenger/taxicab_rate.shtml

[30]Uber discloses its fare system only per mile and it is not clear how many kinks there are within a mile. I just divide the per-mile-fare by 5.

[31]Salnikov et al. (2015 [16]) study which one is cheaper using disclosed Uber API and develop a smartphone app to show their prices.

[32]Function of paying tips within smartphone app was not activated until 2017.

[33]Time charge and surge pricing are not considered. See also Figure 12 in Section 5 for reference.

4 Model and Estimation

4.1 Model Construction

4.1.1 Wait Time and Waiting Passengers

I first construct a model to specify the relationship between unobservable wait time and also the unobservable number of waiting passengers from the equilibrium data. This approach is similar to that of Frechette et al. (2016). There are I locations:{1,...,I} in Manhattan, and each day is divided into hours. Hereafter I reserve i and j for locations, k and l for areas (defined later), and h for hours. From the number of medallions in Manhattan at location i at hour h (N_{ih}), the number of trips which depart from location i at hour h (T_{ih}) and average time (minutes) of trips whose pickup location is i and hour is h (m_{ih}), the fraction of vacant taxis at location i at hour h is calculated as $1 - \frac{T_{ih} m_{ih}}{60 N_{ih}}$. I first set the whole number of medallions in Manhattan N_h and assign each location the number of medallions depending on the trips completed in each location. I use the number of medallions which picked up, not dropped off, passengers at location i at hour h to allocate N_h to each location i to obtain N_{ih}, because I don't specify how each driver acts after he/she dropped his/her passengers off.[34] I also assume the number of medallions N_{ih} to be exogenously determined conditional on location and time, and thus search time at location i at hour h (s_{ih}) is not affected by individual drivers' labor supply decision. I justify this assumption considering that drivers with leased cars, which consist of most of the medallions, had to drive at least 9 hours within 12-hour shift until 2015, and thus not so flexible to start or quit driving depending on the market conditions, especially during peak times. Moreover, demand can often be predicted (so drivers can react to it reasonably) and highly correlated with hours and locations which I control.[35] From these numbers, s_{ih} is readily obtained, $s_{ih} = \frac{60 N_{ih}}{T_{ih}} - m_{ih}$.

Next, let the total length of road at location i, L_i, then there are $\frac{N_{ih}}{L_i}$ cabs per mile at location i. If cabs are uniformly distributed within the same location i, then there are $\frac{N_{ih}}{L_i}(1 - \frac{T_{ih} m_{ih}}{60 N_{ih}})$ vacant taxis every mile (A). Lastly, let v_{ih} be average velocity (mph), then it takes $\frac{60}{v_{ih}}$ minutes for each cab to move one mile (B). If passengers appear randomly within location i, then the wait time at location i at hour h (w_{ih}) for those passengers is calculated[36]

[34] Estimation exercised later shows that search time is long enough for some drivers to move to other locations to increase the probability of pickup. There are gaps between the number of pickups and dropoffs at each location and it's almost obvious that some drivers move to other locations after dropoff. According to Buchholz (2016), Pr(picking new passengers up at location i | dropping previous passengers off at location i) is between 0.4 and 0.5, though the definitions of locations and hours are a bit different.

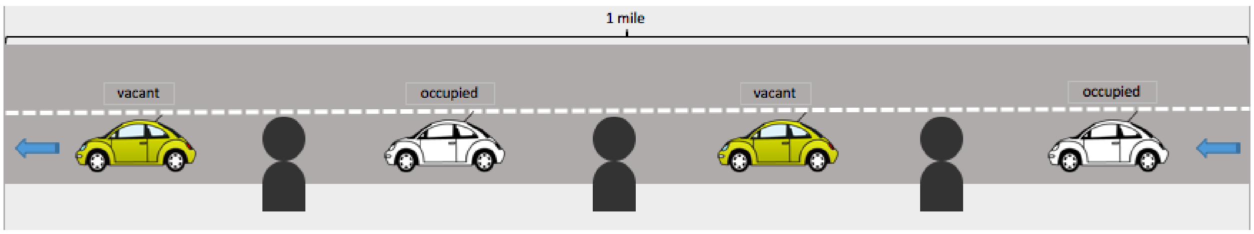
[35] I concisely analyze the supply side with TLC data and show some evidence of inflexible labor supply in Appendix A.

[36] There would be some passengers who could get on yellow cabs just after they appeared and oppositely other people who saw that vacant cabs just passed by, and thus wait time distributes between 0 and $\frac{B}{A}$, so

by $\frac{B}{A}$ and thus, $\frac{60}{\frac{v_{ih}}{L_i}(N_{ih}-\frac{T_{ih}m_{ih}}{60})}$. A simple example is sketched in Figure 7. L_i is by construction exogenous and I assume that m_{ih} and v_{ih} are also exogenous.

Figure 7: Schematic of Location i

If the average velocity is 12 mph and the number of vacant cabs per mile is 2 as in the image at location i at hour h, then wait time is calculated as $\frac{5}{2}$=2.5 minutes.



Furthermore, I relate the equilibrium number of trips (T_{ih}) to the proxy for the number of waiting passengers at location i at hour h (Q^d_{ih}) without any other endogenous variables. I set Q^d_{ih} as in Equation (2) below, where v^H is the fastest velocity in Manhattan for each day. This comes from the simple idea that as the number of cabs per mile is higher and as the velocity is closer to the maximum, the gap between the number of waiting passengers and those who got on taxis would be smaller. I also set P_{ij} the price or fare of trips from location i to j in dollars, and δ_{ij} the distance between the two locations in miles for later use.

The equations of wait time (reprint) and proxy for the number of waiting passengers at location i at hour h are as follows. I omitted search time because it does not directly enter in the demand curve specified below. The variables discussed are summarized in Table 2.

$$w_{ih} = \frac{60}{\frac{v_{ih}}{L_i}(N_{ih} - \frac{T_{ih}m_{ih}}{60})} \tag{1}$$

$$Q^d_{ih} = T_{ih}\{1 + \frac{L_i}{N_{ih}}(\frac{1}{v_{ih}} - \frac{1}{v^H})\} \tag{2}$$

From these two equations, the relationship between wait time and waiting passengers is

$$w_{ih} = \frac{3600L_i}{v_{ih}(60N_{ih} - \frac{m_{ih}Q^d_{ih}}{1+\alpha_{ih}})} \tag{3}$$

where $\alpha_{ih} = \frac{L_i}{N_{ih}}(\frac{1}{v_{ih}} - \frac{1}{v^H})$

wait time on average would be $\frac{B}{2A}$. But as I don't consider other hindrances when looking for vacant cabs (e.g. there are many traffic lines so that passengers can't get on some vacant cabs), I use $\frac{B}{A}$ instead of $\frac{B}{2A}$.

Table 2: Summary of the Variables Used in the Model

Variable	Meaning
N_{ih}	Number of Medallions at Location i at Hour h
T_{ih}	Number of Trips Departing from Location i at Hour h
m_{ih}	Time of Trips Departing from Location i at Hour h (min.)
L_i	Road Length at Location i (mile)
v_{ih}	Velocity of Cabs at Location i at Hour h (mph)
v^H	Fastest Velocity in the Day (mph)
s_{ih}	Search Time at Location i at Hour h (min.)
w_{ih}	(Unobservable) Wait Time at Location i at Hour h (min.)
Q^d_{ih}	(Unobservable) Number of Waiting Passengers at Location i at Hour h
P_{ij}	Price of Trips from Location i to j (dollar)
δ_{ij}	Distance between Location i to j (mile)

4.1.2 Demand Curve

Using the relationship built above, I specify the demand curve as in Equation (4). By this functional form, I assume that the elasticities of demand with respect to price and wait time to be constant. This assumption is relaxed later when I introduce cross terms of those with dummy variables of pickup/dropoff locations. While Frechette et al. (2016) use demand curve with no identification of locations, Buchholz (2016) adopts the curve with time, origin and destination with fixed labor supply, so in that sense, my estimation is similar to that of Buchholz (2016).

$$log(Q^d_{ijh}) = \beta_0 + \beta_1 log(P_{ij}) + \beta_2 log(w_{ih}) + \boldsymbol{\gamma}\mathbf{X_{ijh}} + \epsilon_{ijh} \tag{4}$$

The number of waiting passengers at location i who is heading for location j is just a fraction of the number of trips from location i to j to that of trips where the origin is location i: $Q^d_{ijh} = \frac{T_{ijh}}{T_{ih}} Q^d_{ih}$. Log is natural logarithm, P_{ij} is the price from location i to j as defined above, w_{ih} is wait time for passengers at location i at hour h, and $\mathbf{X_{ijh}}$ is a vector containing other exogenous demand shifters. Importantly, the fare increased in September 2012, so there is a variation of P_{ij}.

ϵ_{ijh} is an error term which is assumed to be independent and identically distributed except for wait time, and this is a crucial assumption to estimate the elasticities without bias. ϵ_{ijh} contains any variables which are not observable or observed but not included in the model, such as income of residents at location i/j or the characteristics of location i/j. I justify the assumption as the following reasoning. Regarding P_{ij}, it is determined outside market by TLC and though passengers can choose from where to where to go, Q^d_{ijh} would not be affected by P_{mn}, as Q^d_{ijh} is not the same as Q^d_{mnh} even if distance δ_{ij} and δ_{mn} are the same (in other words, they are not substitutes each other). As I set locations small enough so that there would be few variations of price within P_{ij}, ϵ_{ijh} would not be correlated with P_{ij}, though each location has some fixed effects.

With respect to w_{ih}, as it is surely correlated with ϵ_{ijh}, I overcome the problem by applying the instrument variable method. I follow the same strategy as Frechette et al. (2016) do, where they use the velocity outside Manhattan as an instrument of wait time. As they point out, traffic velocity outside Manhattan has two opposing effects. One effect is that higher velocity will lower wait time as trips finish faster and thus there are more vacant cabs, while the other is that higher velocity will increase wait time as driving in outer boroughs become more attractive and thus the number of medallions in Manhattan decreases. As I fix the number of medallions in Manhattan constant, only the former effect works in my model.[37]

4.2 Estimation

4.2.1 Properties of Data and Model

I confine the locations of this study to the limited zone where only yellow cabs are allowed to pick passengers up. It is below West 110th street and 96th East street as shown in Figure 8[38]. I will hereafter refer to Manhattan as this yellow cab zone unless otherwise endorsed. I set 50 locations (I=50) which are labeled 0 (Central Park), 1-5 (Upper West Side), 11-16 (Upper East Side), 21-24 (Hell's Kitchen), 31-38 (Midtown), 41-47 (Midtown East), 51-53 (Greenwich Village), 61-64 (Little Italy), 71-74 (East Village) and 81-88 (Lower Manhattan). This classification is approximated to the taxi zones defined by TLC. I name these 50 numbered districts "locations" with suffix i (and j) in the model, and 10 clustered districts written in the parentheses "areas" in this paper. The clustered areas will be important units in the following analyses. Specific location names are written in Appendix B.

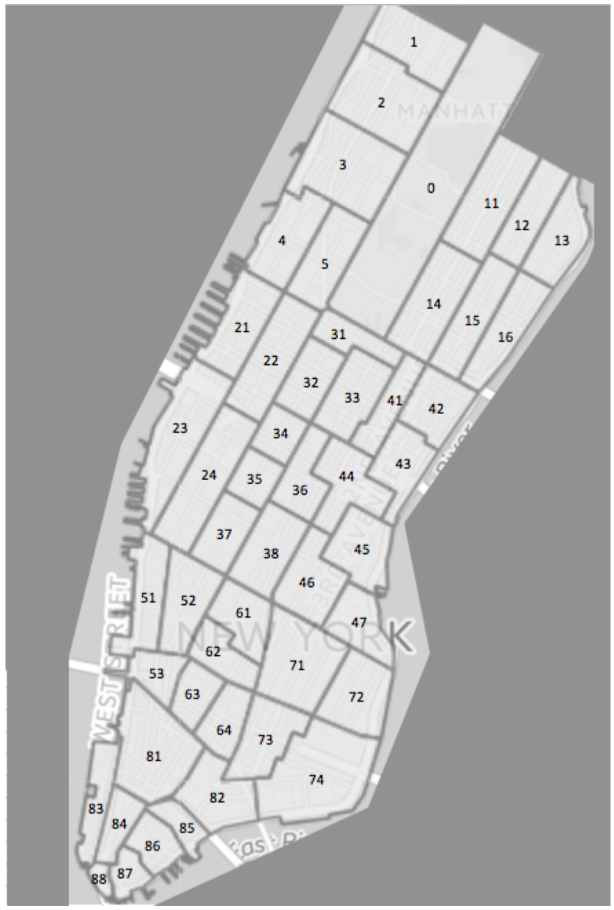
Regarding hour, I set 5 hours (from hour 18 to 22, on the pick-up time basis) as a single unit firstly because these hours are peak hours and thus most medallions are working[39] and secondly because trips are very similar during those hours within a day and the fact contributes to thickening the number of trips with fewer errors. Figure 9 shows the average

[37]Estimation in the next subsection certainly shows that the coefficient of velocity outside Manhattan is significantly negative.

[38]I made this map using the NYU Spatial Data Repository. https://geo.nyu.edu/catalog/nyu_2451_36743

[39]I don't have a panel identifier as Frechette et al. (2016) did, so I don't have precise information how many medallions are working for each location at a specific hour. Therefore, I choose to use only peak hours in order to minimize errors in the number of medallions.

Figure 8: Locations in Manhattan



number of daily trips of a typical month (July 2012).[40] The number of pickups is diverge depending on the locations. While there are about 5,000 daily pickups during the 5 hours near Rockefeller Center (Location 33), there is almost no pickup at North Cove Marina[41] (Location 83).

I set the number of medallions in Manhattan 8,000. This number comes from the fact that more than 70% taxis are working during the peak hours[42] and about 88% of trips depart in Manhattan (yellow cab zone) during the peak time on weekdays. As the number of medallions is 13,437 (as of 2013), I set it 8,000 ($\approx 13,437 \times 0.7 \times 0.88$).[43]

In this study, I don't take into consideration the unique characteristics of taxis that several passengers can share their trips and split the bill. According to the data, approximately two-thirds of trips are solo and the average number of passengers per trip is 1.73. Comparing

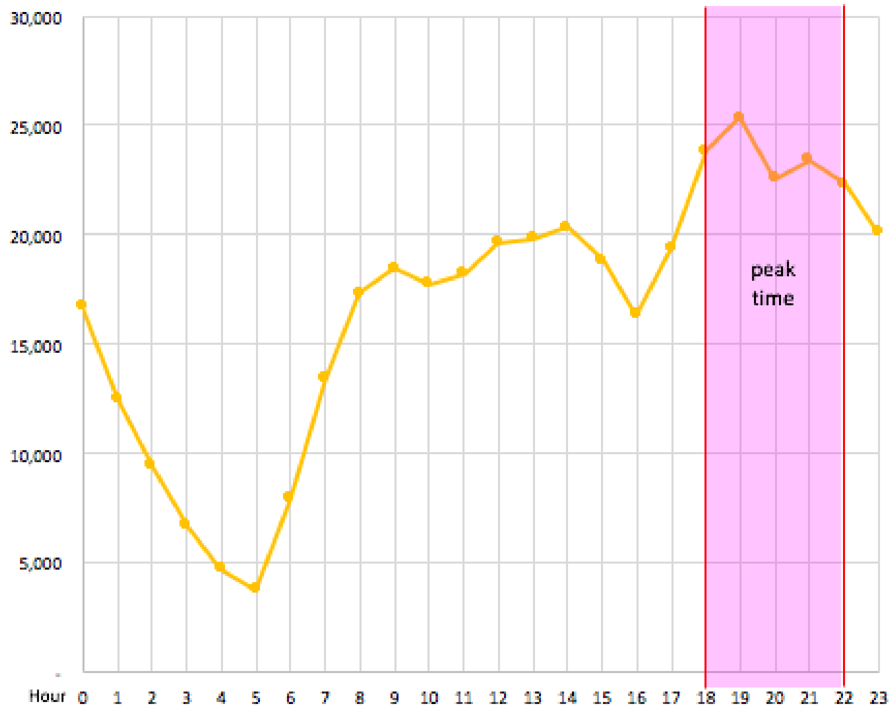
[40]The trough before the peak time is considered due to the supply side when many leased cabs end day-shifts. This is known as the "witching hour."

[41]Second worst is Battery Park (Location 88) with only 30 daily pickups.

[42]Source: Frechette et al. (2016)

[43]I checked that result is only slightly changed if I alternate it with 7,000 or 9,000. See Appendix C.

Figure 9: Number of Pickups in Manhattan



the number of passengers per trip before and after the price increase, the distribution almost didn't change and therefore it would be no problem not to consider the number of passengers per trip in the following analyses.

Road length ranges from 1.5 miles (Battery Park, Location 88) to 16.0 miles (Lower East Side, Location 74). As each road has 2 directions, I multiply it by 2 to use as L_i.[44] Using weekday data of July 2012, velocity is mainly between 9 and 18 miles per hour depending on the locations and days in Manhattan, and the traffic is often slow in Midtown (Location 30's) and Little Italy (Location 60's). On the other hand, the velocity of trips outside Manhattan is between 17 and 20 mph and relatively stable. Average trip time is 9.7 minutes. These statistics are summarized in Table 3.[45]

From these numbers, search time, wait time and the number of waiting passengers can be calculated. Search time is 9.6 minutes on average (median is 8.8 minutes) and wait time is 1.9 minutes on average (median is 1.0 minute).[46] Most of the search time range from 4 minutes to 18 minutes, while wait time mainly from less than 1 minute to 6 minutes.

[44] I therefore assume that passengers don't pick up taxis on the other side even if vacant. See Appendix B for the road length of each location. Source: Google Map.

[45] Summary of data from hour 18 to 22 (based on pickup time) in July 2012

[46] Statistics of wait time and search time are not weighted by the number of trips, so the number of observations is 50 (locations) $\times$ 31 (days) less missing/omitted ones. Fare, distance and trip time are weighted and the number of observation is 2,877,906.

Table 3: Summary of the Statistics

	Mean	S.D.	25 %ile	Median	75 %ile
Fare ($)*	7.75	3.77	5.30	6.90	9.30
Distance (mile)	1.84	1.37	0.99	1.50	2.30
Trip Time (min.)	9.66	5.76	6	9	12
Number of Daily Trips inside Manhattan	92,836	13,845	84,532	94,815	105,123
Velocity (Inside Manhattan, mph)	11.85	4.69	8.80	11.33	14.25
Velocity (Outside Manhattan, mph)	18.95	1.12	18.20	18.73	20.11
Wait Time (min.)	1.94	3.09	0.67	1.02	1.75
Search Time (min.)	9.64	4.37	6.40	8.78	12.20

*Fare composes of base fare, distance fare/time charge. Miscellaneous surcharges are omitted.

Regarding the number of passengers, using the average fastest speed (v^H, which is at hour 5 and approximately 20 mph), it's just less than 1% higher than the actual trips. This would be reasonable considering that the average wait time is as short as 1.9 minutes and more than half of yellow cabs are vacant.[47]

4.2.2 Demand Curve Estimation

I estimate how price and also wait time affect the number of passengers using data of June and July in 2012 and 2013. TLC raised fare in September 2012 and thus 2012 is the year before the fare increase while 2013 is after that.[48] I use data of June and July so that passengers have enough time to recognize the fare increase and I avoid data of August as boro taxis are introduced in August 2013. Though they can't operate in yellow cab zones, this emergence would have influenced yellow cab driver's supply in Manhattan, which I assume is fixed constant. Furthermore, as there is a clear difference regarding trips trend between weekdays and weekends, I choose to use only weekdays (Monday through Thursday).[49] There are 69 weekdays during the 4 months and 2,500 combinations of routes, but there are many routes where there were no trips on some days, so the actual number of observations is 54,947.[50] Though fare is determined exogenously, as wait time is a result of high demand

[47] Rough calculation shows that each cab has passengers for $\frac{9.66\,(average\ trip\ minutes) \times 18{,}567\,(average\ hourly\ trips)}{8{,}000\,(number\ of\ medallions)}$ =22.4 minutes per hour on average during the peak hours.

[48] P_{ij} is the average of each trip's fare between location i and j. Since price is determined outside the market, there is no concern of division bias.

[49] This is the same strategy as Frechette et al. (2016)

[50] I also omitted unrealistic observations where wait time is negative or longer than 20 minutes. These consist only 1.5%.

and also can be a cause of low demand, there is a problem of endogeneity and thus I implement instrument variable approach as stated in 4.1.2.

In Equation (4), $\boldsymbol{\gamma}\mathbf{X_{ijh}}$ are velocity inside Manhattan, distance between location i and j, dummy variables of days, weather (if it rained for more than or equal to 2 hours during the peak hours[51]), clustered pickup and dropoff areas (Upper West Side, Upper East Side, Hell's Kitchen, Midtown, Midtown East, Greenwich Village, Little Italy, East Village and Lower Manhattan). Dummy variables of pickup/dropoff at Central Park are omitted to avoid exact collinearity.

Table 4: Elasticity of Demand w.r.t Own Price and Wait Time

	(1) *log (Waiting Passengers)*	(2) *log (Waiting Passengers)*
log (Price)	-0.437***	-0.386***
	(0.0686)	(0.0686)
$log\,(\widehat{Wait\,Time})$	-0.146*	-0.0943
	(0.0662)	(0.0659)
N	54,947	54,947
R^2	0.207	0.214
Public Transportation Effect	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$log(w_i)$ is instrumented by velocity outside Manhattan and the coefficient is significantly negative as expected in 4.1.2. I control public transportation effects in another regression, where I additionally include in $\boldsymbol{\gamma}\mathbf{X_{ijh}}$ such variables as whether there are subway stations in pickup locations, whether there are subway stations in dropoff locations, whether it is possible to move by subway without changing trains, and whether the origins/destinations are close to Penn/Grand Central stations. This additional regression reflects the idea that outside options would be different for different routes.

Table 4 shows the regression results. Both of the elasticities of demand with respect to price and wait time are significant when public transportation effect is not taken into consideration. Once controlled for the effect, wait time becomes insignificantly different from 0 but the sign is still negative as expected. Controlling for transportation slightly lowers the estimations of the elasticities. Demand is price inelastic and this is intuitive as yellow cabs are often used as important transportation in Manhattan and there was no close substitute

[51]Source: Network for Environment and Weather Applications, Cornell University http://newa.cornell.edu

Table 5: Elasticity of Demand w.r.t Own Price with Cross Terms

		(1)		(2)	
log (Price)		-0.392***	(0.0738)	-0.112	(0.0753)
$log\,(\widehat{Wait\,Time})$		-0.180**	(0.0661)	-0.130*	(0.0659)
log (Price) ×	*Pickup Upper West Side*	0.127***	(0.0185)	-0.0755***	(0.0213)
	Pickup Upper East Side	0.250***	(0.0205)	0.101***	(0.0220)
	Pickup Hell's Kitchen	0.0818***	(0.0197)	-0.0421*	(0.0211)
	Pickup Midtown	0.226***	(0.0184)	0.0504*	(0.0208)
	Pickup Midtown East	0.286***	(0.0184)	0.131***	(0.0203)
	Pickup Greenwich Village	0.0330	(0.0238)	-0.0999***	(0.0247)
	Pickup Little Italy	0.0965***	(0.0206)	-0.0889***	(0.0226)
	Pickup East Village	0.0168	(0.0191)	-0.132***	(0.0206)
	Pickup Lower Manhattan	-0.0615**	(0.0225)	-0.267***	(0.0248)
	Dropoff Upper West Side	-0.234***	(0.0193)	-0.323***	(0.0218)
	Dropoff Upper East Side	-0.353***	(0.0221)	-0.405***	(0.0232)
	Dropoff Hell's Kitchen	-0.0616**	(0.0206)	-0.113***	(0.0219)
	Dropoff Midtown	-0.315***	(0.0193)	-0.388***	(0.0218)
	Dropoff Midtown East	-0.217***	(0.0191)	-0.283***	(0.0210)
	Dropoff Greenwich Village	-0.177***	(0.0248)	-0.247***	(0.0257)
	Dropoff Little Italy	-0.396***	(0.0216)	-0.491***	(0.0237)
	Dropoff East Village	-0.141***	(0.0197)	-0.211***	(0.0212)
	Dropoff Lower Manhattan	-0.572***	(0.0218)	-0.667***	(0.0238)
N		54,947		54,947	
R^2		0.206		0.212	
Public Transportation Effect		No		Yes	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

like Uber at that time. Regarding wait time, it is very inelastic and this might reflect the simulation result that wait time is shorter than 2 minutes in most cases and thus few people would have given up finding vacant cabs.

I also checked whether the price elasticity is dependent on distance, as the percentage of price increase is higher for longer trips. Dummy variables of pickup and dropoff areas in $\boldsymbol{\gamma}\mathbf{X_{ijh}}$ above are replaced by the cross terms of "$log(Price)$ × pickup/dropoff areas" and regressions are exercised in the same way. The result is in Table 5. Coefficients of the cross terms are also displayed. In this case, $log(Price)$ is price elasticity of the route which passengers are both picked up and dropped off within the area of the central park. Depending on the pickup/dropoff areas there are some variations of price elasticities. See Appendix D for the variance-covariance matrix of the variables and the estimated elasticity for each pickup/dropoff area, which are calculated using the regression result with public transportation effect.

Figure 10: Price Elasticities of Area-to-area Routes

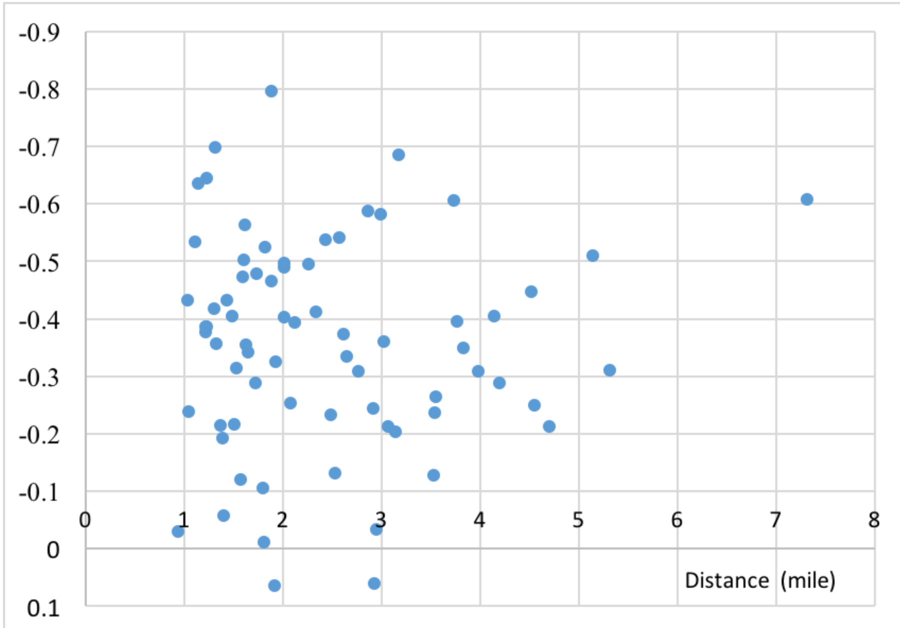


Figure 10 shows the results of price elasticities of area-to-area routes using the regression result with public transportation effects in Table 5 (or Table 17).[52] Horizontal axis is distance and calculated by taking the mean of the distance of trips between (or within) areas. The result is that though price elasticities somewhat depend on origins/destinations of the routes and are mostly between 0.1 and 0.9, the figure suggests that they are not dependent on distance. Correlation is -0.02 and is not statistically significantly different from 0. This evidence supports that the demand for taxis is inelastic for the fare increase by various percentage.

4.3 Welfare Analysis of Price Increase

Next, I calculate how consumer welfare changed before and after the price change. As the demand curve is assumed constant regarding price elasticities conditional on pickup/dropoff locations, even if the price is extremely high, there are few but some passengers who are still willing to pay and thus consumer welfare calculated by simple integration becomes arbitrarily large. Therefore, I instead calculate the lower bound[53] of consumer surplus for each year by

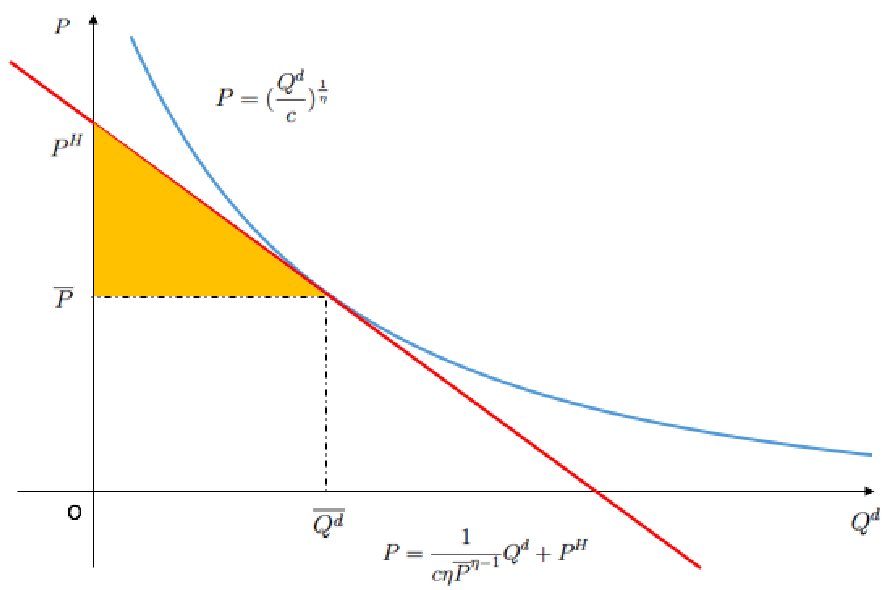
[52]As some area-to-area routes have no trips, the number of points on the figure is less than 100.
[53]Similar approach is adopted in Buchholz (2016)

summing every area-to-area route as in the Equation (5).

$$Consumer\ Surplus = \sum_k \sum_l \frac{1}{2}(P^H_{kl} - \overline{P_{kl}})\overline{Q^d_{kl}} \tag{5}$$

, where k/l are 10 pickup/dropoff areas and P^H_{kl} is the hypothetical highest price passengers would pay for the route from area k to l (explained later), while $\overline{P_{kl}}$ is an average price and $\overline{Q^d_{kl}}$ is the number of waiting passengers, both of which are realized in equilibrium. The image of the consumer surplus is in Figure 11. All of the variables are indexed by kl but are omitted in the figure for ease of reading.

Figure 11: Consumer Surplus by Trips from k to l



The blue curve is the estimated demand curve. Taking exponential of the both sides of Equation (4), and denoting other variables than price c_{kl}, the demand curve can be written as $Q^d_{kl} = c_{kl}P^{\eta_{kl}}_{kl}$, where η_{kl} is the price elasticity of trips from k to l and can be calculated from Table 5 (or Table 17). Solving for P_{kl}, the equation written in the figure is obtained. Taking the derivative of the demand curve with respect to P_{kl} at the realized price $\overline{P_{kl}}$, the red tangent line is calculated as in the figure. P^H_{kl} is the intercept with the tangent line and the lower bound of the consumer surplus is the surface of the orange triangle.

The result is in Table 6. As the number of weekdays (Monday through Thursday) are different between June/July in 2012 and 2013, the consumer surplus during peak hours is shown on a daily basis. It declined from 5.32 million dollars to 5.00 million dollars, or decreased by 6.0%, and the main cause would be the price increase.[54]

Table 6: Comparison of Surplus

Year	Daily Consumer Surplus	Daily Producer Surplus	Total
2012	\$ 5.32 M	\$ 0.26 M	\$ 5.58 M
2013	\$ 5.00 M	\$ 0.38 M	\$ 5.38 M

Producer surplus can also be measured by back-of-the-envelope calculation. I here define the producer surplus as gross fare revenue[55] minus fuel and lease cost.[56] Average daily fare during peak time is \$ 776,000 and \$ 889,000 in 2012 and 2013 respectively. According to TLC Factbook 2014, average fuel economy is 29 miles per gallon, and the gas price is \$3.602 per gallon on average in 2013, and the lease rate cap for night-shift (at least for 9 hours) is between \$115 to \$129.[57] From these data, combined with the number of medallions and average velocity, daily consumer surplus during peak time is roughly calculated as \$264,000 and \$377,000 dollars in 2012 and 2013 respectively. Though price increase brought about higher producer surplus, the rise didn't compensate the loss of consumer surplus, leading to the smaller total surplus.

5 Analysis of Uber's Effects on Taxi Market

5.1 Uber's Effects on Demand for Yellow Cabs

Uber grew dramatically since 2014 in NYC and the phenomenon caused the significant decrease in demand for yellow cabs. See Figure 2 in Section 3. Moreover, Uber cut its fare at the end of January 2016 by approximately 15% in NYC and it perhaps accelerated Uber's expansion. See 3.2.4. In this section, I estimate how Uber's growth and its fare cut affected demand for yellow cabs. I use data from February and March in 2015 and 2016 because the period in 2016 is a timing just after the fare cut and thus would be appropriate for estimation

[54]Note that the consumer surplus is the lower bound and considering also that the standard errors of the elasticities are relatively large, the result is just suggestive.

[55]Miscellaneous surcharges are excluded as they don't go to drivers.

[56]Thus I simplify that all of the medallions are leased.

[57]Lease rate cap depends on day/night shift and day.
See http://www.nyc.gov/html/tlc/downloads/pdf/fleet_drivers_rights_poster.pdf

of the price elasticity at the time when Uber was rapidly expanding.[58] I estimate the demand curve of yellow cabs with consideration of Uber's rise as follows.

$$log(Q^d_{ijh}) = \beta_0 + \beta_1 log(UberTrip_{ih}) + \beta_2 log(w_{ih}) + \gamma X_{ijh} + \epsilon_{ijh} \tag{6}$$

This equation is similar to that in the previous section, but different in that 1) yellow cabs fare didn't change during the time period, so the variable is omitted, and 2) I add $log(UberTrip_{ih})$, the number of trips completed by Uber starting from location i. As TLC doesn't provide data on dropoff locations of trips by Uber, I just use information of pickup locations to calculate $log(UberTrip_{ih})$. From the pricing system Uber discloses, the theoretical fare of δ_{ij} without surge pricing can be calculated, but as it is highly correlated with $log(UberTrip_{ih})$, and the coefficient of the fare would overestimate cross price elasticity, I omit them for the sake of higher precision of regression. Hence, I consider the effect of the fare cut not directly, but indirectly using the regression result. Like wait time, the number of trips by Uber is also suspected endogenous because yellow cabs and Uber would be substitutes. Thus I instrument the variable with velocity outside Manhattan and also dummy variable of the year being 2016. $\boldsymbol{\gamma}\mathbf{X_{ijh}}$ are the same as before. I also change the number of medallions[59] from 8,000 to 9,000, considering that the number of boro taxis increased after its introduction and thus the situation outside yellow cab zones should have become more competitive, leading more yellow cabs to drive in Manhattan.[60] I have checked again in Appendix C that this change doesn't affect the main results.

The regression result is in Table 7. Both of the elasticities are significant and the inclusion of public transportation effect has few impact. The elasticity of demand for yellow cabs with respect to Uber trips being approximately 0.17, which roughly shows the number of trips by yellow cab decreases by 1 for every 6 trips by Uber, suggests that Uber (and perhaps other ride-hailing services) generates new demand for door-to-door transportation rather than depriving passengers of yellow cabs. The result is compatible with the data shown in Section 3 that the total demand for taxi-like transportation actually increased from approximately 500,000 to 700,000 between 2013 and 2016.

Regarding the wait time elasticity, it is still below 1, but is much greater compared to

[58]Furthermore, TLC changed the way of disclosure of locations in July 2016 so the data of the second half of the year would not be pertinent in this case.

[59]Buchholz (2016) also analyzes the effect of boro taxis by adding 1,000 yellow cabs into inner Manhattan.

[60]Restrictions on supply flexibility for minifleets and owner-operated medallions (see 3.1.1) were removed, so that yellow cab drivers might have responded to market conditions elastically and could lead to the violation of the assumption. As I have no data on labor supply, I keep assuming that the number of medallions is fixed and invariant to date as before.

Table 7: Elasticity of Demand w.r.t Uber's Trips and Wait Time

	(1)	(2)
	log (Waiting Passengers)	*log (Waiting Passengers)*
$log\,(\widehat{Uber\,Trip})$	-0.168***	-0.166***
	(0.0188)	(0.0187)
$log\,(\widehat{Wait\,Time})$	-0.247***	-0.223**
	(0.0724)	(0.0721)
N	55,244	55,244
R^2	0.242	0.252
Public Transportation Effect	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that in 2012/2013 when Uber was not so popular. See Table 4 in the previous section. This result still remains unchanged even if I don't increase the number of medallions by 1,000 in Manhattan. This implies that as Uber has become considered by passengers as the substitute for yellow cabs, they might wait for yellow cabs less patiently than before.

As before, I also exercise regression replacing dummy variables of pickup and dropoff areas in $\boldsymbol{\gamma}\mathbf{X_{ijh}}$ above with the cross terms of "$log(UberTrip)$ $\times$ pickup/dropoff areas" to check whether the elasticity of demand for yellow cabs with respect to Uber Trips are dependent on distance, as whether Uber actually cut its fare depends on it due to the application of minimum fare. Table 8 shows the result and Figure 12 depicts the relationship between the distance of trips and the elasticities using the regression result with public transportation effects in Table 8. There are two important thresholds of distance. One is whether the minimum fare ($7) is applied to Uber trips and the second is whether Uber is cheaper than yellow cabs. See also 3.2.4. The figure indicates that there is almost no relationship between distance and the elasticity of demand with respect to Uber Trips. This result indirectly suggests that Uber's fare cut[61] itself didn't decrease demand for yellow cabs, though it might have increased demand for Uber itself. In fact, Uber was already cheaper than yellow cabs even before fare cut conditional on minimum fare not being applied and hence there were few passengers who began to use Uber instead of yellow cabs just because the fare decreased. Furthermore, this supports the conclusion above that Uber mainly generated new demand rather than taking them from yellow cabs.

[61] I assume here that the fare is just determined by the disclosed fare system and no surge pricing is exercised. According to Cohen et al. (2016), fare surged for less than 20% of trips during the 5 hours from Monday to Thursday on average.

Table 8: Elasticity of Demand w.r.t Uber's Trips with Cross Terms

		(1)		(2)	
$log(\widehat{Uber\,Trip})$		-0.265***	(0.0193)	-0.226***	(0.0195)
$log(\widehat{Wait\,Time})$		-0.183*	(0.0726)	-0.240***	(0.0725)
$log(\widehat{Uber\,Trip}) \times$	*Pickup Upper West Side*	0.182***	(0.00695)	0.134***	(0.00815)
	Pickup Upper East Side	0.223***	(0.00704)	0.194***	(0.00773)
	Pickup Hells Kitchen	0.148***	(0.00687)	0.130***	(0.00749)
	Pickup Midtown	0.219***	(0.00609)	0.184***	(0.00707)
	Pickup Midtown East	0.243***	(0.00625)	0.217***	(0.00719)
	Pickup Greenwich Village	0.152***	(0.00816)	0.126***	(0.00855)
	Pickup Little Italy	0.175***	(0.00718)	0.135***	(0.00797)
	Pickup East Village	0.133***	(0.00691)	0.101***	(0.00763)
	Pickup Lower Manhattan	0.143***	(0.00830)	0.102***	(0.00915)
	Dropoff Upper West Side	-0.0393***	(0.00648)	-0.0580***	(0.00718)
	Dropoff Upper East Side	-0.0879***	(0.00756)	-0.0965***	(0.00783)
	Dropoff Hells Kitchen	-0.0239***	(0.00698)	-0.0302***	(0.00730)
	Dropoff Midtown	-0.0914***	(0.00639)	-0.106***	(0.00712)
	Dropoff Midtown East	-0.0724***	(0.00631)	-0.0799***	(0.00685)
	Dropoff Greenwich Village	-0.0618***	(0.00831)	-0.0746***	(0.00852)
	Dropoff Little Italy	-0.130***	(0.00732)	-0.151***	(0.00788)
	Dropoff East Village	-0.0135*	(0.00672)	-0.0263***	(0.00708)
	Dropoff Lower Manhattan	-0.181***	(0.00753)	-0.201***	(0.00805)
N		55,243		55,243	
R^2		0.244		0.247	
Public Transportation Effect		No		Yes	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

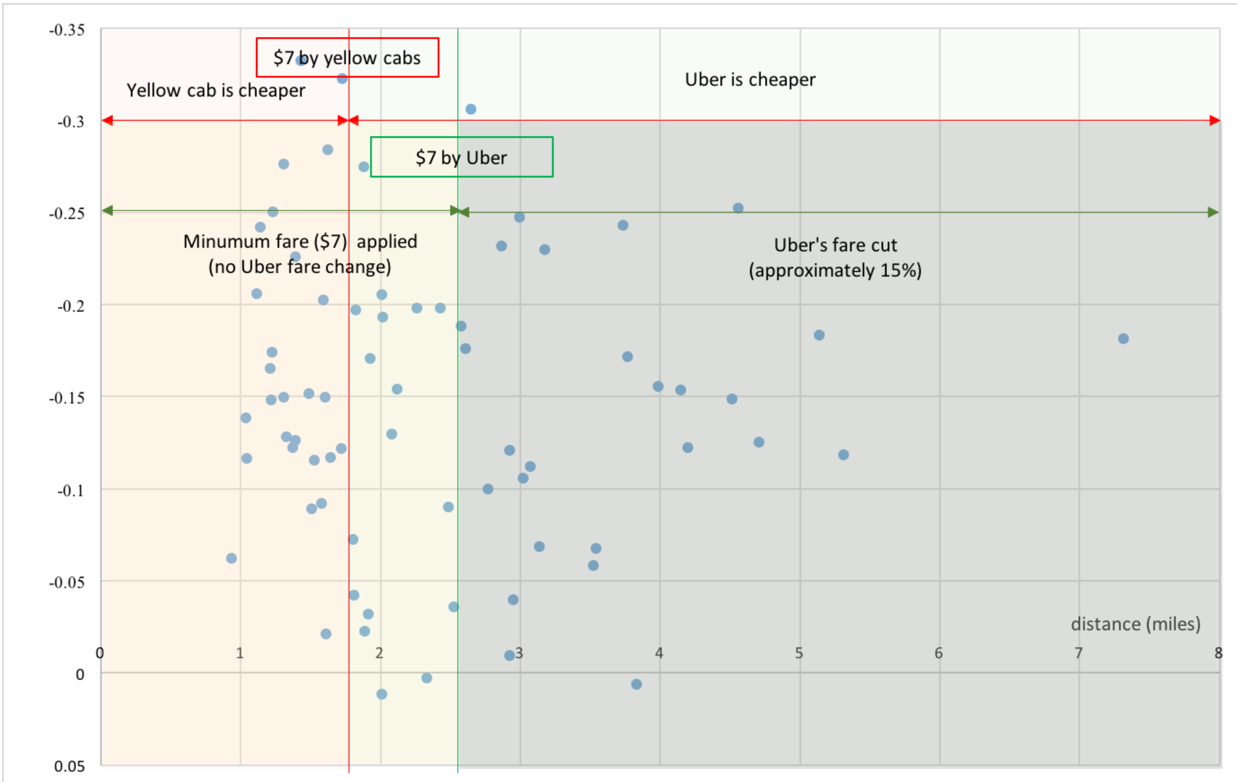
5.2 Welfare Analysis of Uber's Rise

I measure consumer surpluses of yellow cabs and Uber as in 4.3, but as there was no price change after 2015 and no data regarding Uber's dropoff locations, I instead use wait time rather than price to calculate the consumer surpluses.[62] I first exercise a regression with cross terms to estimate the pickup-location dependent elasticity of demand with respect to wait time and estimate the elasticity for each pickup area as in Table 9[63]. The method of calculation of consumer surplus is the same as shown in 4.3, but as I don't have sufficient data on Uber's trips, I assume that wait time, as well as the elasticities of demand with respect to the wait time for yellow cabs and Uber are identical and also that all trips by Uber

[62]It's still possible that I use price elasticity estimated in the previous section to measure the consumer surplus, but it is likely that they have changed due to the rise of ride-hailing services.

[63]The regression result and the variance-covariance matrix of the variables with public transportation effect to derive the elasticity for each pickup area are in Table 18 and Table 19 in Appendix D.

Figure 12: Estimate of Uber's Effect



starting in Manhattan end within Manhattan. Daily consumer surpluses during the peak time of both yellow cabs and Uber for each year are summarized in Table 10. The consumer surplus of yellow cabs declined by 13 % while that of Uber more than tripled, resulting in the total consumer surplus in 2016 being much higher than that in 2015.[64] This shows that Uber generated new consumer surplus and is an evidence that ride-hailing services contribute to the higher social welfare.[65]

6 Concluding Remarks

I have estimated the elasticities of demand for yellow cabs with respect to own price and wait time by constructing the model to connect the relationship between unobservable wait time and the number of waiting passengers with trip data in the NYC taxi market. Both of them are inelastic, which implies that taxis are important public transportation for New

[64] As driver's labor supply is fixed in this model, producer surplus using search time cannot be calculated.

[65] Note again that as these consumer surpluses are lower bound, I impose some assumptions and I don't consider producer surplus and externalities like congestion, the result is just suggestive.

Table 9: Elasticity of Demand w.r.t Wait Time for Each Pickup Area

		Elasticity	
Pickup Area	Central Park	-0.502*	(0.248)
	Upper West Side	-0.443**	(0.137)
	Upper East Side	-0.140	(0.168)
	Hell's Kitchen	-0.652***	(0.143)
	Midtown	-0.802***	(0.110)
	Midtown East	-0.220	(0.130)
	Greenwich Village	-1.021***	(0.205)
	Little Italy	-0.921***	(0.153)
	East Village	-0.545***	(0.146)
	Lower Manhattan	-0.908***	(0.156)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Daily Consumer Surplus by Yellow Cabs and Uber

Year	Yellow Cabs (min.)	Uber (min.)	Total (min.)
2015	7.82 M	3.51 M	11.33 M
2016	6.86 M	11.96 M	18.82 M

Yorkers at least when there were no ride-hailing services. I have also calibrated how Uber, the leader of ride-hailing services, affected the demand for yellow cabs. The estimated result that the elasticity of demand with respect to wait time for yellow cab is larger suggests that Uber is a substitute for yellow cabs to some extent. Uber certainly deprived some passengers of yellow cabs, but it rather successfully generated new demand for door-to-door mobility services. Moreover, Uber's fare cut per se seems to have few impact on decrease of demand for yellow cabs, supporting that the growth of ride-hailing service doesn't come from disruption of taxi markets but rather from new demand hike. Lastly, ride-hailing services have expanded the total consumer surplus to a great extent.

Note that there are some limitations in this study, many of which are due to data constraints. Firstly, I set the number of medallions in each location in Manhattan conditional on hours constant, and thus taxi drivers don't change their labor supply decision both in extensive and intensive manner. The principle of their decision might play a crucial role especially after ride-hailing services became popular and miscellaneous regulation regarding medallions' shifts were abolished. I don't have individual trip data of Uber with respect to dropoff locations, distances or surge pricing. I also don't know which service is provided by Uber, resulting in the assumption that all of the services are operated by UberX. Lack of these information restricts the explanatory power of my model, especially the cross price elasticity for yellow cabs. Much richer data in quality would make it possible to estimate the properties of both supply and demand curves of taxis in a general equilibrium model and the influence of ride-hailing services on the market.

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A Supply Side Analysis: Labor and Taxicabs

Though it is difficult to estimate the driver's labor supply due to lack of panel identifier in the TLC data, there are some incidents or events that might have changed driver's decision of their labor supply. In fact, the days of the least number of trips completed by yellow cabs and also by Uber in 2015 and 2016 were 27th January and 23rd January respectively, when blizzards attacked NYC and the subway was partly closed. The number of trips by yellow cabs decreased by 67% and 78% on the days in 2015 and 2016 respectively, compared to daily average of those months, while the equivalents by Uber decreased by 58% and 62%. As the data shows only equilibrium, it's impossible to distinguish the cause of the dramatic decrease in trips between demand and supply side. However, while the effect of demand side is ambiguous because people would have ceased to go out due to the arrival of a blizzard, but those out of home would have demanded more taxis and partial closure of the subway might have accelerated it, the supply unambiguously declined. It is interesting that the degree of the decrease is smaller for Uber and one of the main causes would be attributed to Uber's surge pricing system, which gives incentives to drivers to work during bad conditions.

Another interest is whether medallions will move to areas where demand temporarily increases expectedly. The following analysis is intended to compare the trips completed by yellow cabs with those by Uber studied in Hall et al.'s paper (2015 [17]). They study how the number of active cars changed on a specific date (21st March 2015) in the vicinity of Madison Square Garden, whose capacity is about 20,000 persons and where pop star Ariana Grande had a sold-out concert. Due to high demand, Uber fare hiked by 1.8 times at highest for over an hour, and responding to these high wages, drivers moved to the area and thus supply almost doubled. They also show that average wait time was almost unchanged before and after demand hike; 2.6 minutes. I have checked whether the number of trips by yellow cabs near Madison Square Garden changed during the peak hours (2 hours from hour 22, based on pickup time). The result is that though the number of trips was slightly higher than average during the month, no significant difference can be found.[66] I have also checked that the ratio of the number of trips on that day during 2 hours from hour 22 to other hours remained almost unchanged, compared to the counterparts of other days or locations. These imply that though waiting passengers might have increased, the number of medallions just didn't increase much or longer search time (queuing for passengers) caused by the increase of yellow cabs bounced matching back to the normal level. This might be because 1) drivers can't expect a long ride as opposed to trips from airports, 2) the taxi stop area near Madison

[66] The area of Madison Square Garden defined in Hall et al. is somewhat large; 5 avenues long and 15 streets wide. I use narrower area (Location 35 in Figure 8) and wider area (Location 24, 34, 35, 37). The result is invariant to the different definitions.

Square Garden is relatively small, 3) Penn station is so close that passengers didn't try to get on taxis so eagerly, and/or 4) expecting this, drivers didn't head for Madison Square Garden. This evidence would constitute one of the pieces of justification that I fix the number of medallions in my model.

B Locations and Road Length

Table 11: Locations and Road Length

Location ID	Area	Location	L_i
0	Central Park	Central Park	18.0
1	Upper West Side	Manhattan Valley	25.4
2		Upper West Side North	19.2
3		Upper West Side South	26.4
4		Lincoln Square West	13.2
5		Lincoln Square East	15.0
11	Upper East Side	Upper East Side North	23.4
12		Yorkville West	16.2
13		Yorkville East	12.4
14		Upper East Side South	26.0
15		Lenox Hill West	18.0
16		Lenox Hill East	9.0
21	Hell's Kitchen	Clinton West	14.4
22		Clinton East	17.4
23		West Chelsea/Hudson Yards	23.2
24		East Chelsea	17.4
31	Midtown	Midtown North	9.4
32		Times Sq/Theatre District	12.6
33		Rockefeller Center	18.4
34		Garment District	7.8
35		Penn Station/Madison Sq West	9.0
36		Midtown South	17.6
37		West Village	11.4
38		Flatiron	15.2
41	Midtown East	Midtown East	13.0
42		Sutton Place/Turtle Bay North	15.2
43		UN/Turtle Bay South	10.8
44		Murray Hill	19.6
45		Kips Bay	11.2
46		Gramercy	18.6
47		Stuy Town/Peter Cooper Village	6.0
51	Greenwich Village	Greenwich Village North	8.8
52		Greenwich Village South	14.2
53		Hudson Sq	8.6
61	Little Italy	Union Sq	11.6
62		Bloomingdale	8.8
63		SoHo	11.6
64		Little Italy/NoLiTa	12.8
71	East Village	East Village	17.8
72		Alphabet City	23.8
73		Chinatown	17.6
74		Lower East Side	32.0
81	Lower Manhattan	TriBeCa/Civic Center	20.2
82		Two Bridges/Seward Park	7.2
83		North Cove Marina	3.8
84		World Trade Center	10.4
85		Seaport	4.0
86		Financial District North	10.4
87		Financial District South	9.6
88		Battery Park	3.0

C Robustness Check

The following tables show the regression result of the elasticities of demand for yellow cabs with respect to own price and wait time, replacing the number of medallions (N=8,000) in Section 4 by 7,000 or 9,000 and checked robustness. Compared to the results presented in Table 4, the main results below hold the same.

Table 12: Elasticity of Demand w.r.t Own Price and Wait Time (N=7,000)

	(1)	(2)
	log (Waiting Passengers)	*log (Waiting Passengers)*
log (Price)	-0.494***	-0.429***
	(0.0704)	(0.0704)
$log\,(\widehat{Wait\,Time})$	-0.170**	-0.117*
	(0.0584)	(0.0582)
N	52,857	52,857
R^2	0.197	0.205
Public Transportation Effect	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Elasticity of Demand w.r.t Own Price and Wait Time (N=9,000)

	(1)	(2)
	log (Waiting Passengers)	*log (Waiting Passengers)*
log (Price)	-0.380***	-0.327***
	(0.0678)	(0.0678)
$log\,(\widehat{Wait\,Time})$	-0.221**	-0.170*
	(0.0798)	(0.0795)
N	55,657	55,657
R^2	0.213	0.219
Public Transportation Effect	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Next, the tables below show the regression result of the elasticities of demand for yellow cabs with respect to Uber's trips and wait time, replacing the number of medallions (N=9,000) in Section 5 by 8,000 or 10,000 and checked robustness. Compared to the results presented in Table 7, the main results below hold the same.

Table 14: Elasticity of Demand w.r.t Uber's Trips and Wait Time (N=8,000)

	(1)	(2)
	log (Waiting Passengers)	*log (Waiting Passengers)*
$log\,(\widehat{Uber\,Trip})$	-0.168***	-0.165***
	(0.0187)	(0.0186)
$log\,(\widehat{Wait\,Time})$	-0.196**	-0.174**
	(0.0604)	(0.0601)
N	55,095	55,095
R^2	0.241	0.251
Public Transportation Effect	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Elasticity of Demand w.r.t Uber's Trips and Wait Time (N=10,000)

	(1)	(2)
	log (Waiting Passengers)	*log (Waiting Passengers)*
$log\,(\widehat{Uber\,Trip})$	-0.168***	-0.165***
	(0.0187)	(0.0186)
$log\,(\widehat{Wait\,Time})$	-0.297**	-0.266**
	(0.0854)	(0.0850)
N	55,277	55,277
R^2	0.243	0.253
Public Transportation Effect	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Auxiliary Tables

Table 16: Variance-Covariance Matrix of Table 5

		log (Price)	log (Price) × Pickup Area									log (Price) × Dropoff Area								
			0's	10's	20's	30's	40's	50's	60's	70's	80's	0's	10's	20's	30's	40's	50's	60's	70's	80's
log (Price)		5.665																		
log (Price) × Pickup Area	0's	-0.363	0.453																	
	10's	-0.306	0.350	0.484																
	20's	-0.376	0.352	0.312	0.444															
	30's	-0.350	0.363	0.321	0.358	0.435														
	40's	-0.345	0.360	0.331	0.338	0.353	0.414													
	50's	-0.319	0.343	0.307	0.375	0.365	0.330	0.609												
	60's	-0.334	0.367	0.323	0.378	0.393	0.350	0.398	0.511											
	70's	-0.326	0.360	0.320	0.345	0.352	0.341	0.342	0.361	0.423										
	80's	-0.448	0.406	0.353	0.405	0.372	0.369	0.425	0.407	0.379	0.615									
log (Price) × Dropoff Area	0's	-0.394	0.009	0.027	-0.005	-0.002	0.000	-0.002	0.003	0.002	-0.003	0.475								
	10's	-0.384	0.029	-0.019	0.036	0.026	0.033	0.038	0.033	0.041	0.053	0.357	0.539							
	20's	-0.479	0.000	0.032	-0.034	-0.018	0.008	-0.063	-0.048	-0.013	-0.064	0.385	0.334	0.479						
	30's	-0.535	-0.008	0.027	-0.020	0.001	0.008	-0.014	-0.013	-0.015	-0.021	0.408	0.355	0.397	0.476					
	40's	-0.544	0.005	0.019	0.015	0.013	0.023	0.013	0.016	0.017	0.016	0.387	0.357	0.368	0.393	0.440				
	50's	-0.538	0.005	0.037	-0.060	-0.017	0.011	-0.110	-0.052	-0.009	-0.100	0.381	0.338	0.414	0.402	0.365	0.660			
	60's	-0.559	0.005	0.035	-0.052	-0.015	0.010	-0.053	-0.039	-0.008	-0.050	0.413	0.356	0.419	0.428	0.389	0.439	0.563		
	70's	-0.496	0.004	0.036	-0.011	-0.006	0.011	-0.008	-0.004	0.008	-0.008	0.395	0.338	0.381	0.392	0.375	0.378	0.403	0.447	
	80's	-0.566	0.012	0.038	-0.054	-0.017	0.012	-0.098	-0.048	-0.003	-0.073	0.413	0.354	0.430	0.425	0.389	0.462	0.461	0.405	0.567

Note: The unit of the variance/covariance is 10^{-3}.

0's: Upper West Side 10's: Upper East Side 20's: Hell's Kitchen 30's: Midtown 40's: Midtown East

50's: Greenwich Village 60's: Little Italy 70's: East Village 80's: Lower Manhattan

Table 17: Elasticity of Demand w.r.t Own Price for Each Pickup/Dropoff Area

		Dropoff Area									
		Central Park	Upper West Side	Upper East Side	Hell's Kitchen	Midtown	Midtown East	Greenwich Village	Little Italy	East Village	Lower Manhattan
	Central Park	-0.112	-0.435***	-0.517***	-0.225**	-0.500***	-0.395***	-0.359***	-0.603***	-0.322***	-0.379***
		(0.0753)	(0.0732)	(0.0737)	(0.0720)	(0.0712)	(0.0708)	(0.0724)	(0.0715)	(0.0716)	(0.0714)
	Upper West Side	-0.187*	-0.510***	-0.593***	-0.301***	-0.575***	-0.471***	-0.434***	-0.678***	-0.398***	-0.454***
		(0.0734)	(0.0714)	(0.0722)	(0.0701)	(0.0692)	(0.0689)	(0.0706)	(0.0696)	(0.0697)	(0.0696)
	Upper East Side	-0.011	-0.334***	-0.417***	-0.125	-0.399***	-0.294***	-0.258***	-0.502***	-0.222**	-0.278***
		(0.0744)	(0.0726)	(0.0726)	(0.0716)	(0.0707)	(0.0702)	(0.0721)	(0.0711)	(0.0712)	(0.0710)
	Hell's Kitchen	-0.154*	-0.477***	-0.559***	-0.267***	-0.542***	-0.437***	-0.401***	-0.645***	-0.365***	-0.421***
		(0.0732)	(0.0709)	(0.0721)	(0.0693)	(0.0687)	(0.0688)	(0.0694)	(0.0685)	(0.0692)	(0.0684)
Pickup Area	Midtown	-0.062	-0.384***	-0.467***	-0.175*	-0.449***	-0.345***	-0.308***	-0.552***	-0.272***	-0.328***
		(0.0735)	(0.0713)	(0.0723)	(0.0699)	(0.0693)	(0.0691)	(0.0703)	(0.0694)	(0.0696)	(0.0693)
	Midtown East	0.019	-0.304***	-0.387***	-0.095	-0.369***	-0.264***	-0.228**	-0.472***	-0.192**	-0.248***
		(0.0734)	(0.0712)	(0.0723)	(0.0702)	(0.0694)	(0.0692)	(0.0707)	(0.0697)	(0.0698)	(0.0696)
	Greenwich Village	-0.212**	-0.535***	-0.617***	-0.325***	-0.600***	-0.495***	-0.458***	-0.703***	-0.422***	-0.479***
		(0.0751)	(0.0729)	(0.0740)	(0.0709)	(0.0708)	(0.0708)	(0.0707)	(0.0705)	(0.0712)	(0.0698)
	Little Italy	-0.201**	-0.524***	-0.606***	-0.314***	-0.589***	-0.484***	-0.447***	-0.692***	-0.411***	-0.468***
		(0.0742)	(0.0721)	(0.0731)	(0.0702)	(0.0699)	(0.0699)	(0.0706)	(0.0703)	(0.0704)	(0.0696)
	East Village	-0.244***	-0.567***	-0.650***	-0.358***	-0.632***	-0.528***	-0.491***	-0.735***	-0.455***	-0.511***
		(0.0737)	(0.0716)	(0.0727)	(0.0702)	(0.0694)	(0.0694)	(0.0707)	(0.0697)	(0.0701)	(0.0697)
	Lower Manhattan	-0.379***	-0.702***	-0.784***	-0.492***	-0.767***	-0.662***	-0.625***	-0.870***	-0.589***	-0.646***
		(0.0734)	(0.0712)	(0.0725)	(0.0691)	(0.0689)	(0.0690)	(0.0690)	(0.0688)	(0.0695)	(0.0684)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Elasticity of Demand w.r.t Wait Time with Cross Terms

		(1)		(2)	
$log\,(\widehat{Uber\,Trip})$		-0.208***	(0.0195)	-0.202***	(0.0193)
$log\,(\widehat{Wait\,Time})$		-0.816**	(0.249)	-0.502*	(0.248)
$log\,(\widehat{Wait\,Time}) \times$	*Pickup Upper West Side*	0.383	(0.273)	0.0585	(0.271)
	Pickup Upper East Side	0.601*	(0.289)	0.362	(0.287)
	Pickup Hells Kitchen	0.0156	(0.276)	-0.151	(0.274)
	Pickup Midtown	-0.00234	(0.260)	-0.300	(0.258)
	Pickup Midtown East	0.567*	(0.269)	0.282	(0.267)
	Pickup Greenwich Village	-0.352	(0.313)	-0.519	(0.310)
	Pickup Little Italy	-0.180	(0.281)	-0.419	(0.279)
	Pickup East Village	0.177	(0.277)	-0.0428	(0.275)
	Pickup Lower Manhattan	-0.103	(0.283)	-0.406	(0.281)
N		55,244		55,244	
R^2		0.178		0.192	
Public Transportation Effect		No		Yes	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Variance-Covariance Matrix of Table 18

		$log(\widehat{WaitTime})$	$log(\widehat{WaitTime}) \times$ Pickup Area									
			Upper West Side	*Upper East Side*	*Hell's Kitchen*	*Midtown*	*Midtown East*	*Greenwich Village*	*Little Italy*	*East Village*	*Lower Manhattan*
$log(\widehat{WaitTime})$		0.0613									
$log(\widehat{WaitTime}) \times$ Pickup Area	*Upper West Side*	-0.0579	0.0733								
	Upper East Side	-0.0578	0.0579	0.0825							
	Hell's Kitchen	-0.0578	0.0579	0.0578	0.0748						
	Midtown	-0.0578	0.0579	0.0579	0.0579	0.0665					
	Midtown East	-0.0578	0.0579	0.0578	0.0579	0.0579	0.0712				
	Greenwich Village	-0.0577	0.0579	0.0578	0.0579	0.0579	0.0579	0.0964			
	Little Italy	-0.0578	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0777		
	East Village	-0.0578	0.0579	0.0578	0.0578	0.0579	0.0579	0.0579	0.0579	0.0757	
	Lower Manhattan	-0.0580	0.0579	0.0579	0.0578	0.0579	0.0579	0.0578	0.0579	0.0579	0.0791