2018

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March 31, 2018

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This research was supported, in part, under National Science Foundation Grants CNS-0958379 and CNS- 0855217 and the City University of New York High Performance Computing Center at the College of Staten Island.

Submission date: March 31, 2018

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We empirically examine the effect of Uber's presence on the demand for medallion taxi trips in New York City. We estimate the percent change in number of Yellow and Green cab trips given a one percent change in number of Uber rides – the elasticity - using rainfall as an instrumental variable. City-wide, Uber rides supplement, rather than replace, Yellow and Green cab rides. For Yellow cabs, this result is powered by the area of Manhattan below 110^{th} street, however during the morning rush only, Uber rides replace yellow cab rides there. These suggests Uber competition will have quite different effects in markets depending upon the thickness and vigor of the existing taxi market and site-specific commuting patterns.

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1 Introduction

Uber, the leading smartphone app based ride-hailing company, has been touted for the efficiency of its service. The benefits to both passengers and drivers have recently been examined by Cohen et al. (2016), Cramer and Krueger (2016), Hall and Krueger (2016),and Chen et al. (2017). In the meantime, Uber has experienced temporary bans from major cities such as London, Delhi, India, and Austin, Texas. Critics have assailed Uber for opaque p assenger safety requirements, increased traffic congestion, labor practices regarding its "driver-partners," and its surge pricing policies. Another critical issue, that has not been well-studied, is Uber's impact on existing taxi cab services. Evaluating whether Uber competition is a threat to the traditional taxi industry will inform the strategies of Uber and cities with disputes.

New York City (NYC) has a large and well established taxi market, appropriate as an experimental field to conduct research on Uber's impact. The NYC Taxi & Limousine Commission (TLC) has regulated the medallion cab service (Yellow cabs) for almost fifty years. Recently, TLC launched a new medallion cab service, called street hail livery (SHL, or Green cabs).[1] In 2015, the medallion taxi fleet comprised 7,676 Green cabs and 13,587 Yellow cabs (TLC 2016 page 1).[2]

Specifically, we estimate the percent change in Yellow and Green cab trips given a one percent change in Uber rides – the elasticity- using NYC medallion taxi trip records and Uber pick-up records from April to September 2014, and January to June 2015. We use rainfall as an instrumental variable to control for endogenous factors affecting medallion taxi demand in a taxi trip demand model.

The Uber–rides elasticity of demand for Yellow cab rides for the entire New York City area is about 4.7%, 9.1% for Green cab rides. These GMM estimates have strong statistical significance and sufficiently small overidentification test statistics.

[1] Green cabs are restricted from picking up passengers in the core Manhattan zone (below West 110^{th} Street and East 96^{th} Street), and at the two NYC airports (TLC 2013). Other than this restriction, TLC regulations are the same for both Yellow and Green cabs.

[2] See TLC (2016) for more NYC taxi statistics.

We find that the distribution of rides across the boroughs differs for Yellow Cabs, Green Cabs, and Uber cars. Figure 3(a) shows the proportion of Yellow cab rides relative to the sum of all three types of rides in each zip code, 3(b) the proportion for Green cab rides, and 3(c) for Uber rides. Yellow cabs predominate in the core Manhattan zone, below West 110th Street and East 96th Street, and at the airports, Green cabs in the Bronx and in patches of Brooklyn and Queens. Uber cars predominate in some of the outer areas of the Bronx and Queens, and parts of Staten Island. We therefore disaggregate the data into boroughs and divide Manhattan into the areas above and below 110th Street. The Uber-ride elasticity estimate of demand for Yellow cab rides is statistically significant only in Manhattan below 110^{th} Street, about 4.1%. By looking at the median daily trip statistics in Table 3, in addition, 91% of City-wide Yellow cab trips and 70% of City-wide Uber trips occurred in Manhattan below 110^{th} Street.

We also disaggregate the data by time of day and weekday/weekend. In Manhattan below 110^{th} Street, we estimate a -2.1% Uber-ride elasticity during the morning rush hour between 6 am and 9 am on weekdays, and 3.9% during the weekend. The negative coefficient for the Uber elasticity in Manhattan below 110^{th} Street during the morning rush hour implies that Uber rides replace, rather than supplement, medallion taxi trips during the rush in the central business district of Manhattan In the boroughs outside Manhattan, we estimate 4.6% Uber elasticity during the morning rush hour, and 9.7% during the weekend, suggesting that Uber rides supplement, rather than replace, medallion taxi trips during the morning rush outside Manhattan, and on the weekends.

We observe an opposite pattern in the Uber elasticity of Green cab trip demand. In the outer boroughs, we find statistically significant Uber-ride elasticities of about 5.3% during the morning rush hour, and -6.5% during the weekend. This result can be interpreted as, for Green cab passengers, Uber rides supplement Green cab rides during the morning rush hour, but replace them during the weekend. However, the overidentification test statistics for Uber-ride elasticity estimates by different times of day and weekday/weekend are too large to accept them as supporting evidence.

The studies most closely related to our topic, on the supply side of the taxi market, are Farber (2015) and Brodeur and Nield (2016). They examine the NYC cabdrivers' labor supply, the well-known behavioral economics topic established by Camerer et al. (1997), Farber (2008), and Crawford and Meng (2011). Farber (2015) revisits the issue and shows that the wage elasticity of NYC cabdrivers' labor supply is positive, consistent with the prediction of the neoclassical labor supply model. He finds that when it rains, the number of taxi trips in NYC increases while the total fare income does not change; and shows that cabdrivers' heterogeneous preferences may yield negative wage elasticities. Brodeur and Nield (2016) use a similar research design, and find that the number of daily Uber rides increases on rainy days, suggesting that Uber drivers respond positively to increases in demand. The validity of the instrumental variables in the current investigation relies on the positive effect of precipitation on the number of Uber and medallion taxi rides.

The closely related studies on the demand side of the taxi market are Cohen et al. (2016) and Buchholz (2016). Cohen et al. (2016) utilize a large-scale dataset of individual Uber trip records four U.S. cities, New York, Chicago, Los Angeles, and San Francisco. They use Uber's surge pricing algorithms to identify the price elasticity of demand for Uber rides at each price point, and then calculate the total associated consumer surplus .In the current investigation, we focus on estimating the elasticity of demand for medallion taxis relative to changes in the quantity of Uber rides. Buchholz (2016) investigates the consumer surplus of the taxi market in NYC with respect to search friction and regulated taxi fares with a large dataset of taxi ride characteristics. He shows that if search costs are removed (as they might be if medallion taxis adopted ride-rider matching technologies like Uber's), consumer surplus is doubled by substantially increasing number of daily trips (matching taxi supply to taxi demand).

Random utility maximization has been a predominant model in the travel demand literature, since the seminal work by Domencich and McFadden (1975) and McFadden (1974). We use an aggregate version of the travel demand model, proposed by Peters et al. (2011), to develop a demand model for the count of taxi rides with a single trip mode (taxi), which allows us to estimate the elasticity of demand for taxi trips relative to the quantity of Uber rides. A number of papers have studied the demand for taxi trips using different model specifications: Douglas (1972), De Vany (1975), Beesley and Glaister (1983), Cairns and Liston-Heyes (1996), Arnott (1996), and Flores-Guri (2003). These studies analyze the taxi trip market with the fare as the unit price of the trip, and discuss whether the regulated fare yields the second best in terms of efficiency, given the monopoly pricing in the market which arises due to the use of medallion licensing as an entry control.

Jackson and Schneider (2011) and Schneider (2010) examine New York City taxi drivers' moral hazard which motivates the drivers to engage in risky driving and criminal activities. The unit of observation in these studies, however, is the individual driver's legal record, not individual taxi trips.

2 The Empirical Framework

Our primary goal is to estimate the elasticity of NYC medallion cab demand with respect to quantity of Uber rides. In order to consider spatiotemporal variation, we estimate a panel data model for taxi trip demand

$$y_{it} = \delta \cdot u_{it} + \mathbf{x}_{it}\boldsymbol{\beta} + \gamma_i + \theta_t + c_{it}, \tag{2.1}$$

where y_{it} is the number of NYC medallion taxi trips, u_{it} is the number of Uber trips, $\mathbf{x}_{it}$ is a vector of medallion taxi trip attributes, γ_i and θ_t are location and time specific effects respectively; and c_{it} is the location-time specific error term. The unit of location, NYC zip code, is represented by i, while t represents the time period, hour of day-month-year. To estimate the coefficient of interest, δ, we must control for the endogeneity of the demand for Uber rides and of the medallion taxi trip attributes which stem from the cab drivers' labor supply behavior. We also must account for the non-uniform and nonstationary spatiotemporal variation in the data series of the demand for taxi trips. For y_{it} and u_{it}, we take the log of number of taxi trips and the log of number of Uber trips respectively; therefore the estimate of δ is interpreted as the elasticity of demand for taxi trip rides with respect to the number of Uber rides.

2.1 Data

We use NYC medallion taxi trip records and Uber pick-up records from April to September 2014, and January to June 2015. Medallion cabs' individual trip records are available to the public from the TLC's website. The records have detailed information about individual taxi trips such as pick-up and drop-off date/time, pick-up and drop-off location in GPS coordinates (latitude and longitude), trip distance, itemized fares, number of passengers, etc. Uber does not make its trip records public, so we use data provided by FiveThirtyEight that have pick-up time and location only.

[Table 1 about here.]

Descriptive statistics for the daily taxi trip records are reported in Table 1. Over the sample period, Uber's market share is around 10% of the NYC yellow taxi trip market. In the first row we see the median number of daily pick-ups is about 440,000 for Yellow cabs, 47,000 for Green cabs, and 40,000 for Uber cars (columns 1, 2, and 3). Columns 3 and 4 show the median total taxi fare of daily trips is about 7 million dollars for Yellow cabs, and 700,000 dollars for Green cabs. The median total distance of daily trips is about 1.4 million miles for Yellow cabs, and 136,000 miles for Green cabs (columns 6 and 7). The total number of pick-ups over the sample period, in the bottom row, columns 1, 2, and 3, is about 159 million for Yellow cabs, 17 million for Green cabs, and 19 million for Uber cars.

We aggregate the individual trip records of Yellow cabs, Green cabs, and Uber cars separately by pick-up zip code (location identifier i) and hour-day-month-year (time period identifier t) We then match and merge the records for the three taxi trip services, with unit of observation pick-up zip code and hour-month-year. For Yellow Cabs, Green cabs, and Uber cars from 2014, we assign the 248 unique NYC zip code areas to each individual trip record according to the trip's pick-up geographic coordinates, longitude and latitude. The zip code assignment for Uber pick-up is the same for the 2014 records. Instead of the single point pick-up coordinates, the 2015 Uber records have "taxi *zone* identifiers." We therefore assign zip codes to the 2015 Uber trip records using the zip code area that overlaps most with the taxi zone. The sample period comprises 364 days and 12 months. The total number of time points, hour-day-month-year, is 8,736. With 248 zip code areas assigned to each time point, the total number of observations is 2,166,528.

The rain data that we use for an instrumental variable, produced by the National Centers for Environmental Prediction (NCEP), have 1121 × 881 grids covering the entire U.S. territories on the North American continent. The stage IV weather radar measures three meteorological quantities (reflectivity, radial velocity, and spectrum-width base) in each grid. Hourly precipitation accumulation within each four square kilometer boundary grid is then calculated based on the three quantities. We use the hourly precipitation data for the 189 grids covering New York City in our empirical analysis.[3]

[3] See Hamidi et al. (2017) for more details about the stage IV radar data. Many thanks to Ali Hamidi and Naresh Devineni of the National Oceanic and Atmospheric Administration/Cooperative Remote Sensing Science and Technology Center at the City College of the City University of New York for sharing the data.

2.2 Identification

The regression model (2.1) is a demand model, and therefore controlling for endogeneity due to unobservable supply factors is crucial to identify the parameters in the model. Along with hourly precipitation, we use indicator variables for pick-up zip codes as instrumental variables for the number of Uber trips and the endogenous medallion taxi trip attributes such as trip distance, trip time length, and number of passengers.

We argue that rainfall and the pick-up location of taxi trips are valid instruments because i) taxi trip demand is highly correlated with rainfall; but ii) cab drivers' labor supply is uncorrelated with rain because of the compliance rule for any passengers' trip request. Farber (2015) and Brodeur and Nield (2016) are the first studies of the effect of rain on NYC taxi cab and Uber drivers' labor supply respectively. Farber (2015) finds that taxi demand substantially increases when it rains, but drivers' income does not change. This is due to a decrease in the supply of taxi trips because i) traffic congestion gets worse when it rains; and ii) drivers prefer not to drive in the rain so they tend to stop their shifts early. Brodeur and Nield (2016) document evidence that Uber drivers positively respond to increasing demand when it rains. We therefore infer that the magnitude of the Uber drivers' response is substantially greater than the medallion cab drivers'.

[Figure 1 about here.]

We argue further that taxi trip supply is uncorrelated with rainfall due to the compliance rule. The TLC mandates drivers to accept any trip requests, unless the vehicle is occupied and the passengers do not want to pick-up additional passengers, or the prospective passenger is in possession of an article that would damage the vehicle or leave a stain or foul smell (TLC 2010 Section 2-50(e)(3)). According to the TLC rulebook (Section 2-50(a), "a driver shall not seek to ascertain the destination of a passenger before such passenger is seated in the taxicab."[4]

We find some support for this argument in our data. Precipitation in a given hour-location is almost uncorrelated with the average speed of taxi trips occurring in that hour-location. As shown in Figure 1(a) in log scale, the scatterplot of average taxi trip speed is almost flat with respect to precipitation. We further find that precipitation is positively correlated with the number of taxi trips (0.0081), and negatively correlated with trip distance (-0.0018), trip time length (-0.0040), and total fare (-0.0013) (all in log scale). These correlation coefficients are

[4] See TLC (2010) for more details about cab rules and regulations.

suggestive that taxi trips increase in frequency and decrease in length when it rains; however the magnitudes of the coefficients are too small to be statistically significant, as shown in the first column of the scatterplot matrix in Figure 1(b).

2.3 Spatiotemporal Distribution

It is well-known that econometric estimation with nonstationary data may cause either inconsistent estimation of the target parameter due to serial correlation in the error term, or inefficient standard error estimation due to heteroskedasticity. To control for nonstationarity issues, we apply the first-differencing transformation by day-month- year for all variables in (2.1). Prima facie, the data series of the number of NYC medallion taxi trips and Uber trips are nonstationary over time, due to factors such as whether a driver's shift is a day shift or a night shifts and whether it is rush hour or not. Income targeting on the part of cab drivers, addressed by a number of behavioral economics papers, could also produce nonstationarity in taxi trips. Farber (2015), in particular, demonstrates the time variation in NYC medallion cab trips. He shows that day shift cab drivers have more rigid start times, whereas end times are more rigid for night shift drivers.[5]

[Figure 2 about here.]

To illustrate the daily variation in our dataset that may cause nonstationarity, Figure 2(a) shows time series plots for the number of medallion cab trips and Uber trips by day. Uber trips have a steady growth trend while the plot for medallion cabs is stable. These different long-run trends may prevent the estimation of the causal relationship between the number of Uber trips and the number of medallion cab trips. The scatterplot of first differenced variables in Figure 2(d) shows a clear positive linear relationship, which does not appear in Figure 2(c).

[Figure 3 about here.]

[5] Farber (2015) finds that there are two peaks in the hourly distribution of shift start times, additional evidence that the time variation of taxi trips is nonstationary.

The spatial distribution of the taxi trip data shows that Yellow cabs, Green cabs, and Uber cars serve different areas of New York City. Uber and Green cab pick-ups occur in wider areas than Yellow cab pick-ups. Figure 3 presents NYC taxi zone maps showing the median proportion of daily pick-ups by zip code. The Yellow cab pick-ups mostly occur in the core Manhattan zone and the two airports, whereas Green Cabs and Uber cars have broader pick-up distributions.[6]

3 Empirical Results

[Table 2 about here.]

Table 2 reports estimation results of the model (2.1), with Yellow cab trips in columns 1, 2, and 3, and Green cab trips in 4, 5, and 6. All variables, excluding indicators, are log-differenced from the same zip code-hour-day-month-year hour of 24 hours previous. Since all the variables are in log scale, each coefficient represents the elasticity of the designated cab rides (Yellow or Green) with respect to the corresponding variable.

We find a City-wide Uber-ride elasticity of 4.7% for Yellow cab trips with respect to Uber rides, and 9.1% for Uber-ride elasticity for Green cab trips in the generalized method of moments (GMM) estimations in columns 3 and 6. These positive and statistically significant coefficients imply that Uber rides supplement both Yellow and Green cab trips. In particular, a 1% increase in Uber trips causes a 4.7% increase in Yellow cab trips and a 9.1% increase in Green cab trips. Although the magnitudes differ, the sign and statistical significance of the GMM estimates are the same as those from the OLS specification (columns 1 and 4) and the two-stage least squares (TSLS) specification (columns 2 and 5).

The Uber-ride elasticity of Green cab trips found in Table 2 is twice the size of Yellow cab trips. This difference results from the large disparity in in market share held by Yellow and Green cabs in the five New York City boroughs. As shown in Table 3, about 91% of daily Yellow cab trips and 70% of daily Uber trips occurred in Manhattan below 110^{th} Street, whereas only 7% of Green cab trips occurred in that area.[7] The 4.7% Uber-ride elasticity of Yellow cab trips is therefore powered by rides in Manhattan below 110^{th} Street, and the 9.1%

[6] Recall Green cabs are restricted from picking up passengers in the core Manhattan zone (below West 110^{th} Street and East 96^{th}Street), and at the two NYC airports TLC (2013). This is the reason that Figure 3(b) shows Green cabs with almost no pick-ups in those areas.

[7] For each type of service, find the percent of rides in Manhattan below 110^{th} Street by dividing the total number of rides below 110^{th} Street (in the top row in columns 3, 6, and 9)) by the sum of the numbers in the "Total" column.

Uber elasticity of Green cab trips is powered by rides in Brooklyn and Queens, where 63% of Green cab trips occurred.

The GMM estimates are our preferred results, because this specification controls for the endogeneity of cab drivers' labor supply and the nonstationarity of taxi rides, providing statistically consistent Uber elasticity estimates. In addition, the overidentification (overid) test statistics show that the GMM results do not reject the null hypothesis that the instrumental variables are exogenous. Although the TSLS estimates are qualitatively similar to the GMM estimates, the TSLS overid test statistics strongly reject the null hypothesis of exogeneity. We do not believe these statistics invalidate the instrumental variables. Rather, we suspect that the heteroskedasticity resulting from the nonstationary data causes the rejection of the overidentifying restriction in TSLS.

[Figure 4 about here.]

Examining our data, we find suggestive evidence of heteroskedasticity in the hourly data series for number of taxi trips, which is nonstationary, and is successfully controlled for in Table 2 GMM estimation. The data series for the daily number of taxi trips appears (relatively) stationary in log-differenced form, but the hourly data series does not. Figure 4 shows daily and hourly variations in the number of pick-ups before and after log-differencing. Comparing panels 4(a) and 4(b), the log-differencing appears to make the daily data series stationary, that is, the series randomly fluctuates around zero. The log-differencing for the hourly data series, however, seems to amplify the morning and evening rush hours, causing nonstationarity. In 4(c), the log-scale series declines substantially in the middle of the night. In 4(d) the log-differenced series remains nonstationary, with two peaks, one in the morning rush hour between 6 am and 9 am, and the other at the evening rush hour between 5 pm and 7 pm.

[Table 3 about here.]

3.1 The Effect of Uber Trips on Yellow Cab Trips

[Table 4 about here.]

Table 4, column 1, reproduces the GMM estimates of the Uber-ride elasticity of the demand for Yellow cab trips for all of New York City from Table 2, column 3, and then reports estimates by borough and Manhattan below and above 110^{th} Street. The overid test statistics do not reject the overidentifying restriction, and therefore the instrumental variables are valid for the estimates in Table 4.

We see in column 3 that the 4.7% City-wide Uber-ride elasticity for Yellow cab trips comes mostly from Manhattan below 110^{th} Street, where the Uber-ride elasticity estimate is 4.1%. The elasticity estimate for all of Manhattan is about 3.3%, and in Manhattan above 110^{th} Street, 23%, although neither is statistically significant. Uber trips appear to supplement Yellow cab trips in Manhattan below 110^{th} Street.

The Uber elasticity estimates outside Manhattan are positive but statistically insignificant. The elasticity estimates in Brooklyn and Queens have, however, Z-statistics that exceed one. It is thus too early to conclude that Uber trips have no impact on Yellow cab trip outside of Manhattan below 110^{th} Street. We are unable to estimate the elasticity in Staten Island due to the insufficient number of observations.

In Table 5 we report Uber elasticity estimates for weekday rush hours and on the weekend, in Manhattan below and above 110^{th} Street, and for the other boroughs grouped together. Interestingly, we have a negative Uber elasticity estimate of -2.1% in Manhattan below 110^{th} Street during the morning rush hour, statistically significant at the 5% level. Below 110^{th} Street, the elasticity estimate for the weekend is about 4%, close to the City-wide elasticity of Yellow cab trips. The negative morning rush hour elasticity suggests that Uber trips replace Yellow cab trips at that hour. Note, however that that the overid test statistics for both of these specifications strongly reject the overidentifying restriction. Thus, these two Yellow cab trip samples need to be re-examined with more observations. The elasticity estimate for the evening rush is less than 1% but not statistically significant.

[Table 5 about here.]

3.2 The Effect of Uber on Green Cab Trips

Table 6 reports GMM estimates of the Uber-ride elasticity for Green cab trips during the rush hours on weekdays, on the weekend in Manhattan above 110^{th} Street, and in the other boroughs grouped together. There are no statistically significant Uber-ride elasticity estimates for Green cab trips at any time in Manhattan above 110^{th} Street. In the boroughs outside Manhattan, the Uber elasticity estimate is about 5% during the morning rush hour, and is statistically significant at the 10% level. During the weekend, however, the elasticity estimate is about -6.5% and statistically significant at the 1% level, in contrast to the positive Uber elasticity for Yellow cab trips in Table 5, column 9. The negative elasticity suggests that Uber rides replace Green cab trips in the outer boroughs on the weekend. But this elasticity estimate needs to be re-examined with more observations because the overid test statistic strongly rejects the overidentifying restriction.

[Table 6 about here.]

4. Conclusion

We have empirically examined the effect of Uber's presence on the demand for medallion taxi trips in New York City. Specifically, we estimate the percent change in Yellow and Green cab trips given a one percent change in Uber rides – the elasticity - using NYC medallion taxi trip records and Uber pick-up records from April to September 2014, and January to June 2015. We use rainfall as an instrumental variable in a taxi trip demand model to control for endogenous factors affecting medallion taxi demand. We find that whether Uber's presence supplants medallion taxi rides or increases demand for them depends on location and traffic conditions influenced by time of day and weekday/ weekend status. Our statistically significant results most often show a positive effect of Uber rides on taxi demand. However, Uber pick-ups decrease the number of Yellow taxi rides in Manhattan below 110th Street during the morning rush hour. They also decrease the number of Green cab rides on the weekend in the outer boroughs grouped together.

We view these two results with caution because in both specifications the overidentifying restriction is strongly rejected. But they suggest that Uber competition will have quite different effects in markets depending upon factors such as the thickness and vigor of the existing taxi market and site-specific commuting patterns. Documenting the market characteristics which make the presence of Uber a positive or negative force on the demand for traditional taxis is an important area for future research.

We find that, City-wide, Uber rides supplement, rather than replace, Yellow cab and Green cab rides. For Yellow cabs, the City-wide positive and significant Uber-ride elasticity of the demand for Yellow cab trips is powered by the positive and significant Uber-ride elasticity in Manhattan below 110^{th} Street, where 91% (70%) of daily Yellow cab trips (Uber trips) are initiated. We also estimate the elasticities by borough and by time of day. However, this elasticity differs by time of day. We find a negative and statistically significant coefficient for the Uber-ride elasticity of the demand for Yellow cab trips in Manhattan below 110^{th} Street during the morning rush hour. This coefficient implies that Uber rides replace, rather than supplement, medallion taxi trips during the rush in the central business district of Manhattan, in contrast to other times of day in this area.

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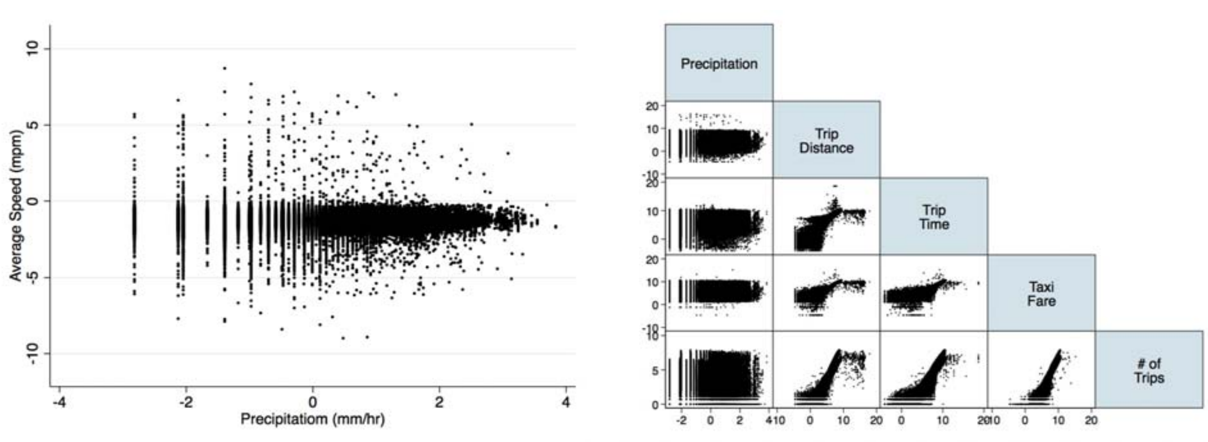
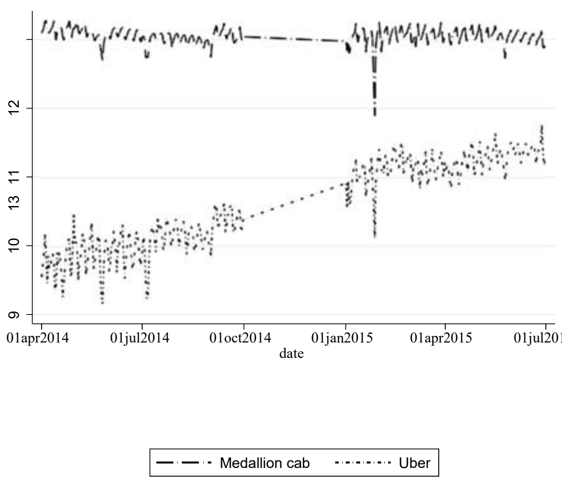


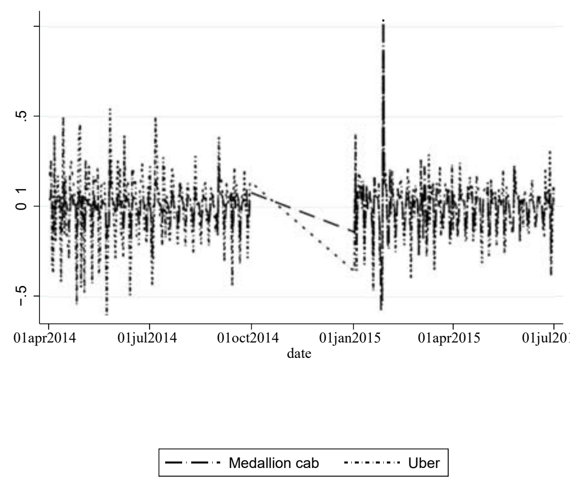
(a) Rainfall and Taxi Speed

(b) Rainfall and Taxi Trip Attributes

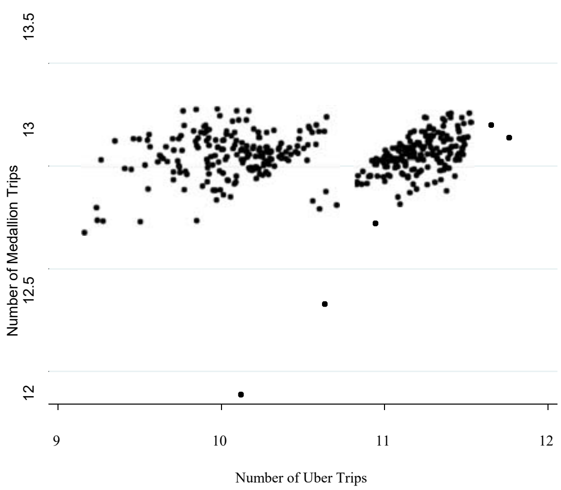
Figure 1: Scatterplot: Rainfall and Taxi Trips (Log-scale)



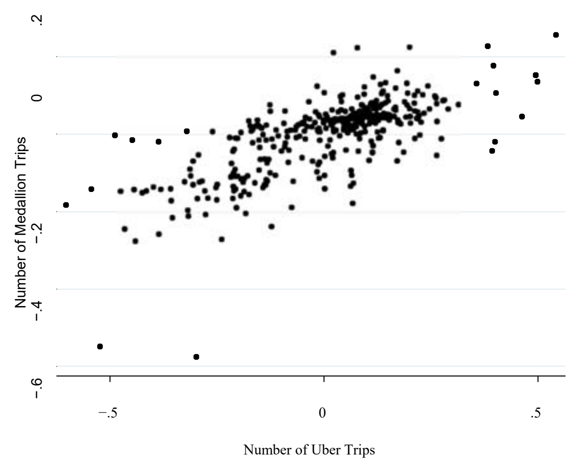
(a) Time Series Plot (Log-scale)



(b) Time Series Plot (Log-differenced)

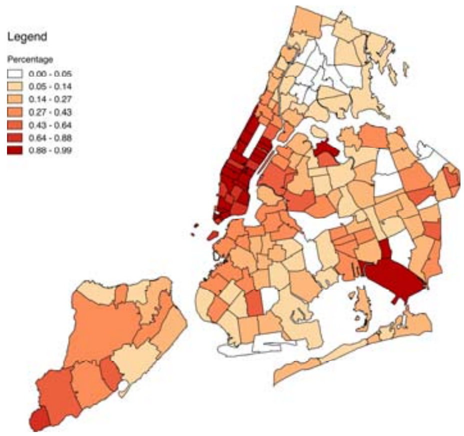


(c) Scatterplot (Log-scale)

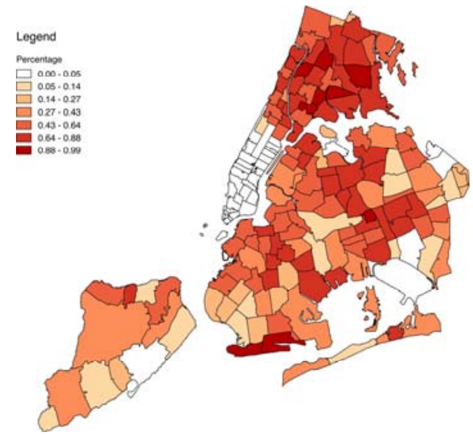


(d) Scatterplot (Log-differenced)

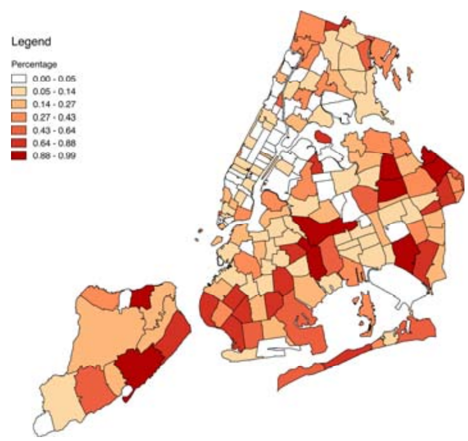
Figure 2: (Aggregate) Time Variation: Medallion Taxi Pick-ups



(a) Yellow cab pick-up

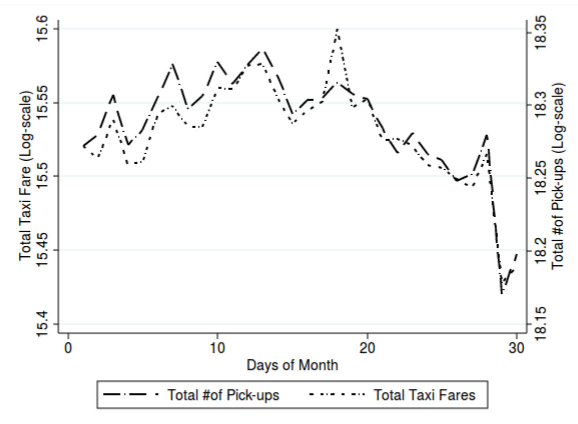


(b) Green cab pick-up

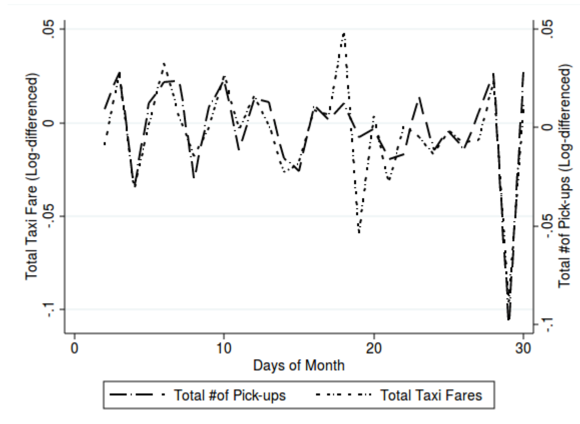


(c) Uber pick-up

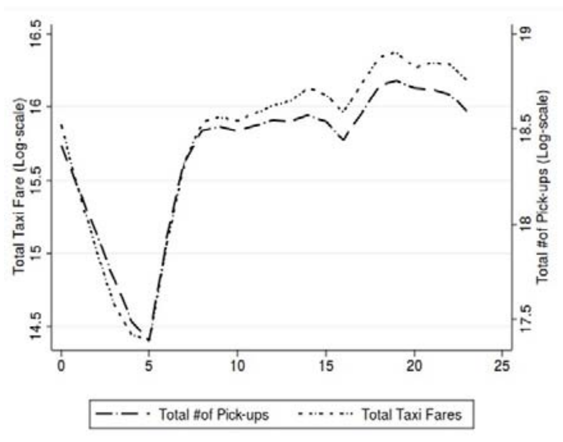
Figure 3: Spatial Distribution: Proportion of Pick-ups for each type of service by Zip code, respectively, relative to the sum of pick-ups by all three services in that zip code



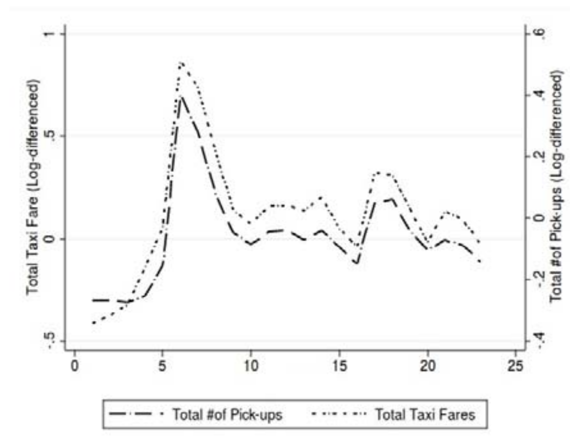
(a) Day of Month (Log-scale)



(b) Day of Month Variation (Log-differenced)



(c) Hour of Day (Log-scale)



(d) Hour of Day (Log-differenced)

Figure 4: (Aggregate) Time Variation: Medallion Taxi Pick-ups

List of Tables

Table 1: Descriptive Statistics

	#of pick-ups			Total Fare		Total Trip Distance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Yellow cab	Green cab	Uber	Yellow cab	Green cab	Yellow cab	Green cab
Median	440,246	47,700	40,520	$6,946,085	$703,083	1,378,623	136,663
Std. dev	53,393.084	14,838.045	29,783.888	$859,212.970	$229,988.996	8,073,866.198	45,088.851
Max	544,519	81,574	136,193	$10,000,912	$1,569,859	60,720,968	244,962
Min	0	0	0	$0	$0	0	0
Total Sum	159,481,189	17,166,393	18,804,806	$2,496,244,821	$254,233,258	1,516,589,012	50,496,604

Note: Std. dev, Max, and Min stand for standard deviation, maximum and minimum value respectively. Median, Standard deviation, Minimum, and Maximum are statistics for rides per day. Total sum is for the entire dataset.

Table 2: Model Estimates with Log-Differenced Variables

	# of Taxi Pickups by hour and zip code					
	Yellow Cab			Green Cab		
	(1) OLS	(2) TSLS	(3) GMM	(4) OLS	(5) TSLS	(6) GMM
Uber (Log-differenced)	0.0242*** [0.000]	0.0706*** (0.017)	0.0466** (0.018)	0.0154*** [0.001]	0.1127*** (0.027)	0.0912*** (0.025)
Trip distance	-0.0895***	-0.2494***	-0.2407***	-0.0906***	0.0543*	0.0212
(Log-differenced)	[0.004]	(0.053)	(0.063)	[0.005]	(0.029)	(0.027)
Trip time (Log-differenced)	0.1017*** [0.002]	0.1044** (0.047)	0.0674** (0.032)	0.0461*** [(0.001]	0.0209 (0.013)	0.0170*** (0.004)
Passengers (Log-differenced)	0.4463*** [0.002]	0.5316*** (0.027)	0.6236*** (0.045)	0.4603*** [0.002]	0.4810*** (0.035)	0.4932*** (0.043)
Meter fare (Log-differenced)	0.4514*** [0.006]	0.5269*** (0.052)	0.4800*** (0.096)	0.4841*** [0.007]	0.3177*** (0.053)	0.3513*** (0.063)
Tip (Log-differenced)	-0.0420*** [0.001]	-0.0469*** (0.004)	-0.0388*** (0.007)	-0.0401*** [0.001]	-0.0359*** (0.004)	-0.0363*** (0.005)
Constant	-0.0238***	-0.0297***	-0.0177**	-0.0243***	0.0065	0.0010
	[0.002]	(0.006)	(0.008)	[0.002]	(0.007)	(0.007)
# of obs	391,181	391,181	391,181	208,385	208,385	208,385
R^2	0.9008	0.8867	0.8787	0.8944	0.8774	0.8837
χ^2 Test Statistic (df)		375.92 (150)	102.70 (150)		276.89 (126)	74.91 (126)
(p-value)		(0.0000)	(0.9988)		(0.0000)	(0.9999)

Notes: Standard errors are reported in parentheses. Heteroskedasticity robust standard errors are reported in square brackets. The symbols, *, **, and *** indicate respectively that the estimated coefficient is statistically significant at the 10%, 5%, and 1% levels. The TSLS and GMM estimates treat "# of Uber pickups", "trip distance", "trip time", and "# of passengers," as endogenous covariates. The instrumental variables are precipitation and the indicator variables for trip origin ZIP Code. The row for χ^2 test, 2^{nd} from the bottom, reports the overidentification test statistics with degrees of freedom in parentheses. The associated p-values are reported in the lowest row in parentheses. Note that all model estimates contains fixed effect indicator variables for i) months, ii) years, and iii) weekdays.

Table 3: Descriptive Statistics: Number of Trips by Borough

	Yellow cab			Green cab			Uber		
	(1) Median	(2) Std. Dev	(3) Total	(4) Median	(5) Std. Dev	(6) Total	(7) Median	(8) Std. Dev	(9) Total
Below 110^{th} *st*	386,145	44,875	139,228,280	3,578	1,025	1,237,478	28,928	18,213	12,489,445
Above 110^{th} *st*	5,234	1,279	1,987,334	10,135	2,710	3,609,152	891	1,132	515,003
Brooklyn	8,356	3,810	3,513,685	16,440	6,567	6,074,914	6,544	5,327	2,811,660
Queens	15,320	2,148	5,563,737	13,023	4,021	4,703,185	2,408	2,858	1,399,821
Bronx	297	117	121,565	3,601	1,144	1,308,222	369	637	254,801
Staten Island	5	4.62	2,064	7	4.94	2,616	15	20	7,992
Airports	8,439	1,169	3,093,857	161	52.1	58,952	828	626	378,678

Table 4: GMM Estimates of Yellow Cab Demand (# of pick-ups)

	Entire sample	Manhattan			Brooklyn	Queens	Bronx
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		All	Below 110^{th}	Above 110^{th}			
Uber	0.0466**	0.0330	0.0407**	0.2278	0.1082	0.1236	0.0344
(Log-differenced)	(0.018)	(0.022)	(0.021)	(0.271)	(0.097)	(0.096)	(0.077)
# of obs	391,181	259,791	228,679	31,112	75,543	46,014	1,785
R^2	0.8787	0.8889	0.9208	0.6974	0.8758	0.8173	0.7541
χ^2 Test (df)	102.70(150)	14.75(63)	9.90(51)	0.81(8)	19.74(32)	21.40(30)	8.49(11)
(p-value)	(0.9988)	(1.0000)	(1.0000)	(0.9992)	(0.9556)	(0.8751)	(0.6690)

Notes: Standard errors are reported in parentheses. Heteroskedasticity robust standard errors are reported in square brackets. The symbols, *, **, and *** indicate respectively that the estimated coefficient is statistically significant at the 10%, 5%, and 1% levels.

Table 5: GMM Estimates for Yellow Cab Trips by Weekday Rush Hour and Weekend

	Manhattan Below 110^{th} st			Manhattan Above 110^{th} st			Other Boroughs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Morning	Evening	Weekend	Morning	Evening	Weekend	Morning	Evening	Weekend
Uber	-0.0207**	0.0041	0.0389***	0.0254	0.1278	-0.0488	0.0458*	0.0443	0.0969***
	(0.010)	(0.009)	(0.008)	(0.141)	(0.118)	(0.086)	(0.024)	(0.028)	(0.028)
# of obs	26,714	24,604	63,605	4,070	3,112	10,115	18,352	11,750	43,390
R^2	0.9309	0.8540	0.9139	0.7698	0.8252	0.7647	0.7194	0.8386	0.7587
χ^2 Test (df)	79.73(49)	41.67(51)	233.41(51)	1.81(8)	3.00(8)	8.79(8)	88.55(70)	74.09(60)	128.71(78)
(p-value)	(0.0036)	(0.8213)	(0.0000)	(0.9863)	(0.9346)	(0.3607)	(0.0665)	(0.1043)	(0.0003)

Notes: Standard errors are reported in parentheses. Heteroskedasticity robust standard errors are reported in square brackets. The symbols, *, **, and *** indicate respectively that the estimated coefficient is statistically significant at the 10%, 5%, and 1% significance levels. Morning (evening) rush hour is between 6 am (5 pm) and 9 am (7 pm) on weekdays.

Table 6: GMM Estimates for Green Cabs by Weekday Rush Hour and Weekend

	Manhattan Above 110^{th} st			Other Boroughs		
	(1) Morning	(2) Evening	(3) Weekend	(4) Morning	(5) Evening	(6) Weekend
Uber	-0.0080	0.0107	-0.0704	0.0526*	-0.0000	-0.0648***
	(0.106)	(0.086)	(0.051)	(0.031)	(0.018)	(0.024)
# of obs	4,346	3,472	10,719	20,802	17,655	52,202
R^2	0.8649	0.6257	0.8953	0.8244	0.7760	0.7799
χ^2 Test (df)	4.23(8)	0.31(8)	5.65(8)	97.81(75)	91.36(78)	208.95(89)
(p-value)	(0.8358)	(1.0000)	(0.6868)	(0.0397)	(0.1430)	(0.0000)

Notes: Standard errors are reported in parentheses. Heteroskedasticity robust standard errors are reported in square brackets. The symbols, *, **, and *** indicate respectively that the estimated coefficient is statistically significant at the 10%, 5%, and 1% levels. Morning (evening) rush hour is between 6 am (5 pm) and 9 am (7 pm) on weekdays.