The Impact of Ride-sharing Services on Traffic Congestion - An Empirical Study on the entry of Uber

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Abstract

The introduction of multi-side sharing economy platforms such as Uber, Lyft and Airbnb have had a profound impact on the way consumers and producers interact, as well as incumbent businesses. The large scale and disruptive effect of these platforms as well as the divergent views on their welfare and societal implications has necessitated the need to study the empirical impact of these platforms. This work uses a difference - in - difference approach to investigate the impact of the entry of Uber - A transport networking, multi-side sharing economy platform on traffic congestion in urban centers in the United States. This work exploits the geographical and temporal variation in the introduction of Uber in various cities in the United States to estimate the effect of its introduction on traffic congestion.

1. Introduction

The past few years have seen the introduction of many technology enabled, multi-side sharing economy platforms such as Uber, Airbnb, TaskRabbit. Etc. The sharing economy is generally defined as a 'peer to-peer-based activity of obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services' (Hamari et al, 2013). These platforms facilitate a new mode of exchange of goods and services, in place of traditional modes of exchange of goods and services where consumers interact with businesses as opposed to fellow consumers, who in the sharing economy act as goods or service providers. For example, the sharing economy platform Airbnb enables users to rent out accommodation at other users homes, while traditionally the default option would have been to seek this same service from the hotel industry. The sharing economy is in it's very nascent stages and is referred to by a variety of different names, some alternative names for the sharing economy include gig economy, platform economy, access economy and collaborative consumption.[1]=

Sharing economy platforms have seen explosive growth in the past few years, this growth is both in terms of the valuations of the companies that own these platforms and in terms of user bases. Uber, one of the earliest player in the sharing economy space, founded in 2009, is currently valued at 70 billion US dollars.[2] A Pew Research center survey estimates that 72% of Americans have used a sharing economy platform at least once and 15% of Americans use

[1] "What Should the 'Sharing Economy' Really Be Called? - The Atlantic." 27 May. 2016, https://www.theatlantic.com/business/archive/2016/05/sharing-economy-airbnb-uber-yada/484505/. Accessed 16 Nov. 2017.
[2] "From zero to seventy (billion) - Uber - The Economist." 3 Sep. 2016, https://www.economist.com/news/briefing/21706249-accelerated-life-and-times-worlds-most-valuable-startup-zero-seventy. Accessed 16 Nov. 2017.

ride-sharing applications such as Uber.[3] The global revenue potential of these sharing economy platforms is estimated to grow to 365 billion US dollars by the year 2025 from the current 15 billion US dollars.[4]

These sharing economy platforms have largely - at least in their initial phases, grown in the shadows of government regulation. The scale at which they operate now and the disruption that they have caused has made them hard to ignore and, increasingly, a target of government regulation and intense public debate about their impact on welfare. This debate has largely taken place in the media, and most arguments, for or against, are often not backed by rigorous quantitative studies of the impact of these platforms. Given the recency of the sharing economy phenomenon, the academic literature in this space is also in it’s infancy, with a body of research slowly emerging.

Uber is widely regarded as the poster boy of the sharing economy movement, it currently operates in 737 cities, in 84 countries across the globe. Within the United States it operates 249 cities, and is the largest ridesharing service with 75% of the market. [5] This rapid rise of Uber has upended the incumbent taxi industry that operated in a regulated fashion, requiring permits and medallions to own and operate taxis. This disruption has been made possible for a variety of reasons. Firstly, Uber and other similar services resolve market failures, by avoiding the bureaucratic processes of licensing and leveraging dynamic pricing (Surge Pricing in Uber speak) they are able to scale or reduce supply with demand more efficiently.

[3] "The New Digital Economy: Shared ...." 19 May. 2016, http://www.pewinternet.org/2016/05/19/the-new-digital-economy/. Accessed 16 Nov. 2017.
[4] "The sharing economy: how will it disrupt your ... - PwC UK blogs." http://pwc.blogs.com/files/sharing-economy-final_0814.pdf. Accessed 16 Nov. 2017.
[5] "Uber Cities → Active in 84 countries, 737 cities - Uber Estimate." https://uberestimator.com/cities. Accessed 16 Nov. 2017.

Secondly, ride-sharing services are able to provide better pricing to the consumer, through a combination of subsidising rides as well as lower operating costs.[6] Thirdly, the method of requesting an Uber via a mobile application connected to the internet reduces the search costs associated with finding a taxi and thus is likely a more preferred option.

The increasing penetration of sharing economy platforms and their impact raises some crucial questions about their societal and economic impact. The impact of these platforms needs to be rigorously studied as the results of these studies will be a key factor in aiding policy makers in designing effective and informed policies to regulate these platforms in the future. Give the fact that Uber has taken center stage in much of the debate that surrounds the societal impact of the sharing economy, more specifically ride-sharing, researchers have begun to explore the effects of Uber in a rigorous empirical manner.

Greenwood & Wattal (2015) use a difference-in-difference approach and find a reduction in drunk driving related vehicular homicide rates after the introduction of Uber in California. Gong, Greenwood & Song (2017) find that the entry of Uber in China leads to an increase in new vehicle registrations by 8 percent. Burtch, Carnahan & Greenwood (2016) study the impact of the introduction of Uber on local entrepreneurial activity and find that it significantly decreases the volume of new entrepreneurial ventures as well as the level of self-employment. The impact of other sharing economy platforms have also been studied in the literature, Zervas, Proserpio & Byers (2017) find that the introduction of Airbnb in Texas has led to a decrease in hotel revenue by 8-10 percent.

[6] "Uber Vs. Taxi Pricing By City - Business Insider." 16 Oct. 2014, http://www.businessinsider.com/uber-vs-taxi-pricing-by-city-2014-10. Accessed 16 Nov. 2017.

Given the rapid rise of Uber and its popularity as an alternative to public transit options and a lower cost substitute for taxi options in urban areas raises important questions about the impact that ride-sharing services have on traffic congestion in urban areas. There are two differing perspectives on this issue; proponents of ride-sharing services argue that the low cost of these services and ease of access will provide a convenient alternative to driving alone and thus reduce traffic congestion and car ownership in the long run. Critics of ride-sharing services, on the other hand, argue that the low cost of ride-sharing services will divert trips from other modes of public transit or non motorized transport to these services and perhaps, introduce new trips altogether. (Alexander and Gonzalez 2015)

The debate on this issue of the impact of ride-sharing services on traffic congestion is far from settled. There are many instances of city specific studies that conclude that the entry of ride-sharing services are increasing traffic congestion. A study by Schaller Consulting[7] estimates that ride-sharing companies added 50,000 vehicles and over half a billion miles of driving in New York. A country wide survey conducted by the UC Davis institute of transport studies points to an increase in both traffic congestion and emissions as a result of the entry of ride-sharing services.[8] The San Francisco police department reported that cars operating on ride-sharing platforms account for two thirds of congestion-related traffic violations. [9] On the other side of this debate, Li, Hong & Zhang (2016) using a difference-in-difference approach find empirical evidence that the introduction of ride-sharing services, specifically Uber, leads to a significant reduction in traffic congestion.

[7] "unsustainable? - Schaller Consulting." http://www.schallerconsult.com/rideservices/unsustainable.pdf. Accessed 4 Dec. 2017.
[8] "New Research on How Ride-Hailing Impacts Travel Behavior - STEPS." https://steps.ucdavis.edu/new-research-ride-hailing-impacts-travel-behavior/. Accessed 4 Dec. 2017.
[9] "SFPD: Uber, Lyft account for two-thirds of congestion-related traffic ...." 25 Sep. 2017, http://www.sfexaminer.com/sfpd-uber-lyft-account-two-thirds-congestion-related-traffic-violations-downtown/. Accessed 4 Dec. 2017.

This paper contributes to this debate by examining the effect of the entry of Uber on traffic congestion in urban areas of the United States using a different source of traffic congestion data. This study is made possible by the fact that the entry of Uber into various cities in the United States is varied temporally, this allows for the use of a difference-in-difference design to examine the impact of the entry of Uber on traffic congestion.

The rest of the paper is organized as follows. Section 2 describes the data in detail as well as the data sources. Section 3 outlines the methodology being used as well as the estimating equation. Section 4 describes the results of the study as well as some further validation of the empirical design of the study. Section 5 presents the conclusion of the paper.

2. Data

The data for this study comes from various sources. First, traffic congestion data is obtained from the Urban Congestion Report (UCR) that is released on a quarterly frequency by the United States department of transportation - Federal Highway Administration. The Urban Congestion Report dataset used in this study contains data from the last quarter of 2008 (October-December) to the last quarter of 2016 (October-December). The Urban Congestion Report was originally produced for 21 urban areas that are classified as Metropolitan Statistical Areas (MSA) by the Census Bureau , from the last quarter of 2008 to the first quarter of 2013. Post this the UCR has been produced for 52 MSA's until the last quarter of 2016. To capture both pre and post Uber entry traffic congestion data in the urban areas, a key requirement for the difference-in-difference design, I restrict the number of cities considered to the 21 urban areas that have data from the last quarter of 2008. The final panel being considered for the analysis thus consists of 660 observations across 20 cities, St Paul, Missouri is dropped due to large gaps in production of the UCR data.

Second, the data on the entry of Uber into the cities being considered in this study have been obtained by hand from the Uber blog. Uber issues a press release on the day of its entry into any new city, which is recorded on its blog.

Third, data on the controls used in this study, GDP per capita is obtained from the Bureau of Economic Analysis (BEA) gross domestic product by metropolitan area data set and population data is obtained from the Census Bureau population data set.

2.1 Dependent Variable

The UCR contains three measures of traffic congestion the Time Travel Index (TTI), Congestion Hours and Planning Time Index (PTI). For the purpose of this study the main dependent variable of interest is the Travel Time Index. This choice is guided by the previous literature in the field as well as the fact that the TTI is a primary measure of interest in the Li, Hong & Zhang (2016) paper on the effect of Uber on traffic congestion.

The Time Travel Index (TTI) as defined by the UCR is '*the ratio of the peak-period travel time to the free-flow travel time. This measure is computed for the AM peak period (6 am to 9 am) and PM peak period (4 pm to 7 pm) on weekdays.*' For example, a TTI value of 1.20 means that a 20 minute free flow trip will take 24 minutes (20 percent longer) during the peak hour.

2.2 Independent Variable

The primary independent variable of interest in this study is a dichotomous treatment indicator variable. This variable takes on a value of 0 or 1; it takes on the value 1 if Uber is present in city j at time t, and the value of 0 if Uber is not present in city j at time t. This variable takes the value of 1 for the first full quarter that Uber is operational in a city.

The Uber ride-sharing platform has a variety of services on offer, a rider has the option to select a particular service when requesting a ride. These services include; Uber Black, a premium town car service, Uber X, a low cost ride-sharing service and Uber Pool, a carpooling service where multiple riders going in the same direction can share a ride. Of interest in this study is the entry of Uber X. The choice of focusing on Uber X, amongst all the other services on offer warrants further discussion. The reasons for this choice are threefold. First, Uber X is a low cost service where drivers use their own personal vehicles to transport passengers, the low cost of this service is the reason for its popularity and its disruptive effect (Greenwood & Wattal 2015). Second, the earliest entry of Uber X is in 2012 (San Francisco), this provides us with sufficient time post the entry of Uber X to examine the effect it has on traffic congestion. Third, this is the primary choice in the existing literature that deals with the impact of ride-sharing services.

In addition to the dichotomous treatment variable, in order to specify a difference-in-difference estimation equation, the other independent variables are time and city fixed effects.

2.3 Controls

The primary controls that are used in this analysis are used to control for variables that may influence Uber's decision to enter a city. These controls are population size and socio-economic level of an urban area, as indicated by GDP per capita.

3. Methodology and Estimating Equation

3.1 Methodology

The fact that the entry of Uber X into different cities is varied temporally allows me to use a difference-in-difference estimation technique to estimate the effect of the entry of Uber X on traffic congestion. This 'natural experiment' type setting for the entry of Uber X has resulted in the use of the difference-in-difference estimation technique as the primary method to estimate the impact of the entry of Uber X on various dependent variables. Greenwood & Wattal (2015) use it to estimate the effect the entry of Uber X has on drunk-driving related vehicular homicide cases in california. Li, Hong & Zhang (2016) use it to estimate the effect the entry of Uber X has on traffic congestion in urban areas of the United States.

The causal identification of the effect of a treatment using a difference-in-difference model for estimation rests on two key assumptions. First, the model assumes that the entry of Uber X into a city - the treatment - is uncorrelated with traffic congestion in the city - the dependent variable in the study. More specifically, in order for there to exist causal identification the entry of Uber X should be random with respect to traffic congestion levels. Second, the model assumes a homogeneous pre-treatment trend between the treated and control observations. (Angrist and Pischke 2008) In this specific case the second assumption means that the entry of Uber X effects traffic congestion in the same manner across all cities.

In addition to these two assumptions, difference-in-difference estimation using panel data leads to serial correlation of residuals, which lead to inconsistent standard errors. This correlation of residuals is corrected by using a strategy of clustering of standard errors at the city level. (Bertrand, Duflo and Mullainathan 2002)

3.2 Estimating Equation

The primary specification that is used in this analysis is as follows.

$$y_{it} = \alpha + \beta \, Uber\ Entry_{it} + \lambda \, Controls_{it} + \theta_i + \gamma_t + \varepsilon_{it}$$

y_{it} , is the level of traffic congestion in each city i at time t as measured by the Time Travel Index (TTI). $Uber\ Entry_{it}$ is the treatment dummy variable that takes on the value 1 is Uber has entered the city i at time t, and 0 otherwise. $Controls_{it}$ are control variables that are specified for each city i at time t. θ_i and γ_t are city fixed effects and time fixed effects, these variables capture non-time varying factors across cities. Finally, ε_{it} is the error term - in order to deal with issues of heteroskedasticity, the standard errors are robust and clustered at the city level.

4. Results

4.1 Baseline Specification Results

The results of the baseline specification of this model are reported in Table 1. Column 1 reports the results without the use of controls and Column 2 reports the results with the use of controls. The controls used in this specification are Population and Per Capita GDP of each city. The choice of these controls are guided by existing literature and studies of the societal impact of Uber. Finally, Column 3 of Table 1 reports the effect of Uber on traffic congestion using a city specific time varying fixed effect, that varies by year. The choice for using a time varying fixed effect warrants further explanation. The original specification that uses just a city fixed effect ignores city specific time trends. However, there may be many factors that affect traffic congestion in a city that vary across time, this term captures these effects for each city.

The main result of interest in these regressions is the coefficient on the entry of Uber. In the case of Column 1, without using controls I find that the entry of Uber causes a 1.1% increase in traffic congestion as measured by the TTI. In the case of Column 2, after adding controls to the specification I find that the effect of the entry of Uber X reduces to a 0.75% increase in traffic congestion as measured by the TTI. Finally, with the inclusion of city specific time varying the effect of the entry of Uber X reduces further to a 0.64% increase in traffic congestion as measured by the TTI. While there is a reduction in standard errors across the three specifications, neither of the coefficients are statistically significant.

The reason for these results can be explained in two ways, first, it could indicate the fact there could potentially be an effect of the entry of Uber X causing a small increasing traffic congestion, but this particular analysis does not use enough data to make this claim with statistical significance. Second, the lack of statistical significance for any of the results could indicate that the entry of Uber X does not have any significant impact on traffic congestion in the cities being considered in this analysis.

In order to take this analysis further, I consider a Sub-Sample analysis. A careful look at the cities being considered in this study reveal large differences across various comparative factors such as population and size. These differences could potentially invalidate a key assumption of the difference-in-difference model, the 'parallel trends' assumption, this assumes that the effect of the treatment - in this case the entry of Uber X will affect every city in the same manner.

4.2 Sub-Sample Analysis

To perform the sub-sample analysis, I partition the dataset into two categories based on cities, these two categories are called big cities and small cities. The cities categorised as big cities are Boston, Chicago, Los Angeles, San Francisco and Seattle. Specifically, the reasons for selecting these cities and flagging them as different from all other cities being considered are as follows. San Francisco and Seattle are large hubs for technology companies, employees of such companies are most likely to be users and early adopters of technology driven ride sharing platforms like Uber. Boston, Chicago and Los Angeles are each large cities in terms of population and are either large in terms of being educational, financial or business hubs as compared to the other cities being studied in the dataset. In order to estimate the coefficients, I use the same estimating equation mentioned in Section 3 on the two sub-samples of data that are created.

The results for this analysis are reported in Table 2. Column 1 reports the results of the Small Cities and Column 2 reports the results of the Big Cities. Similar to the baseline regressions reported in Table 1, the coefficient of interest in this case is the effect of the entry of Uber X. In the case of the small cities, the effect, surprisingly, has a magnitude of almost 0, and is hence negligible. In the case of the big cities, the model estimates that the entry of Uber X causes a 0.42% increase in traffic congestion as measured by the TTI.

Similar to the previous case of the baseline specification, neither of these results are statistically significant. The reasons for this lack of statistical significance can be argued in the same manner as in the case of the baseline specification. It either indicates a lack of sufficient data to make the claim with statistical significance or the fact that Uber X has no effect on traffic congestion as measured by the TTI.

4.3 Relative Time Analysis

A primary assumption of the difference-in-difference model that has been called out earlier is the 'parallel trends' assumption. More formally, this assumes that there is no difference in the pre-treatment trend across all cities being considered in this study.

Despite the lack of statistical significance in the above results, it is a worthy exercise to validate the design of the difference-in-difference set up to ensure that primary concerns about the assumptions made are addressed. More specifically, this moves the analysis beyond a simple correlation to establish that despite the lack of statistical significance there is a causal relationship between the dependent variable and the primary independent variable of interest, the coefficient on the treatment variable - the entry of Uber X.

In order to address this concern I set up a relative time model that is guided by the set up in Greenwood and Agarwal 2015. This model is set up using a series of time dummies which indicate the relative chronological distance between time t and the time Uber X enters a city

j . This model essentially allows for the measurement of the treatment over time. It allows the identification of whether or not a pre-treatment trend exists and consequently whether the entry of Uber X is non random with respect to the dependent variable - traffic congestion.

The estimating equation for this model is as follows:

$$y_{it} = \alpha + \rho'[s_2 * \vartheta] + \lambda\, Controls_{it} + \theta_i + \gamma_t + \varepsilon_{it}$$

Similar to the original specification of the model outlined in section 3. y_{it} , is the level of traffic congestion in each city i at time t as measured by the Time Travel Index (TTI). $Controls_{it}$ are control variables that are specified for each city i at time t . θ_i and γ_t are city fixed effects and time fixed effects, these variables capture non-time varying factors across cities. Finally, ε_{it} is the error term - in order to deal with issues of heteroskedasticity, the standard errors are robust and clustered at the city level. s_2 is a dichotomous variable that indicates if Uber will affect the city j and ρ' contains the relative time parameters that need to be estimated.

The results of the relative time model reported in Table 3 indicate that none of the pre-treatment relative time dummies - rel time (t-x) are significant. This observation validates the difference-in-difference design as no pre-treatment trend exists across the cities being considered in this analysis. Unsurprisingly, similar to the other results from the other models, post-treatment relative time dummies - rel time (t+x) are not significant.

5. Conclusion

The rapid rise of the sharing economy has raised important questions about it's wider societal impact. These questions have prompted an increased interest in empirically studying the effect of these technology platforms on various variables of interest to inform policy decisions. This paper focuses on using a difference-in-difference approach that exploits the geographical and temporal variation in the entry of Uber X in various cities in the United States to study the impact of the entry of Uber X on traffic congestion in urban areas.

The results of this study point to the fact that the entry of Uber X has caused a small increase in traffic congestion, however, the results lack the statistical significance required to make a robust claim. Despite the lack of statistical significance, these results are relevant for two reasons, first, by performing a relative time analysis and validating the choice of empirical design the results in this study can be interpreted as not just a simple correlation between the entry of Uber and its effect on traffic congestion but casual, albeit, still being inconclusive. Second, it points to the fact that the debate on the impact of Uber, or more broadly ride sharing companies on traffic congestion is far from settled.

This study suffers from a variety of limitations, chief amongst them is the paucity of data in the analysis. The results of this study could potentially have been more conclusive if data on traffic congestion was available for more urban areas in the United States, important cities for ride sharing such as New York are not included in the analysis due to a lack of data. The lack of statistical significance of the results could stem from the fact that the effect of ride sharing services such as Uber in this case, have not had the time for their effects to manifest fully. In addition to this, while an attempt has been made with the relative time analysis to establish the absence of a pre-treatment trend and thus point to the exogenous nature of the entry of Uber, there could be other confounding factors that influence the results that need closer examination. Finally, this analysis also does not consider other negative or positive externalities of ridesharing services and thus cannot speak to the overall societal impact.

In the specific case of ride sharing, this analysis restricts itself to studying Uber X, the other case to study - that is not studied here due to the recency of its introduction and as a result lack of data is that of carpooling ridesharing services such as Uber Pool and Lyft Line. These services group passengers travelling in the same direction in the same car and offer lower pricing than Uber X and other competing services. These services, augmented by the algorithms that power them could lead to the sort of efficiency gains both in terms utilization of roadways and cars that lead to significant reductions in traffic congestion.

Given the popularity of these sharing economy services, it is evident that their users derive significant benefits from these services and that these services are here to stay. Future work in this space will be possible with more data, specifically data from the ride sharing services themselves will shed light on relevant issues such as the efficiency of utilization of the resources on these platforms and paint a clearer picture of the societal benefits of these sharing economy platforms.

Table 1

Dependent Variable	(1) TTI	(2) TTI	(3) TTI
Uber Entry Treatment	0.0115	0.00750	0.00648
	(0.0201)	(0.0198)	(0.0174)
Population		0.00229	0.00237
		(0.00157)	(0.00176)
Per Capita GDP		0.000473	0.000397
		(0.000642)	(0.000271)
Constant	1.283***	-0.421	47.63
	(0.0111)	(1.094)	(48.89)
Observations	614	614	614
R-squared	0.771	0.793	0.875
City Fixed Effects	YES	YES	
Time Fixed Effects	YES	YES	YES
City Year Fixed Effect			YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2

Dependent Variables	Small Cities TTI	Big Cities TTI
Uber Entry Treatment	-0.000333	0.0422
	(0.0111)	(0.0881)
Population	0.000776	0.00655***
	(0.000533)	(0.000559)
Per Capita GDP	-0.000797	0.00129*
	(0.000578)	(0.000560)
Constant	1.333***	-7.815***
	(0.398)	(0.784)
Observations	458	156
R-squared	0.824	0.779
City Fixed Effects	YES	YES
Time Fixed Effects	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3

	(1)
Dependent Variable	TTI
rel time (t-6)	0.00515
	(0.0236)
rel time (t-5)	0.0168
	(0.0287)
rel time (t-4)	-0.0100
	(0.0246)
rel time (t-3)	0.00651
	(0.0214)
rel time (t-2)	0.00239
	(0.0167)
rel time (t-1)	0.0320
	(0.0264)
rel time (t+1)	0.0101
	(0.0148)
rel time (t+2)	0.0151
	(0.0231)
rel time (t+3)	0.0743
	(0.0544)
rel time (t+4)	0.0176
	(0.0331)
rel time (t+5)	0.0276
	(0.0399)
rel time (t+6)	0.00874
	(0.0485)
Population	0.00388
	(0.00311)
Per Capita GDP	0.00180
	(0.00139)
Constant	-2.370
	(2.147)
Observations	241
R-squared	0.787
City Fixed Effects	YES
Time Fixed Effects	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4

City	Entry Date (Month, Year)
Boston	Oct-13
Chicago	Apr-14
Detroit	Oct-13
Houston	May-14
Los Angeles	Sep-13
Oklahoma City	Oct-13
Philadelphia	Jun-12
Phoenix	Nov-12
Pittsburg	Mar-14
Portland	Dec-14
Providence	Sep-14
Riverside - San Bernardino	May-14
Sacramento	Feb-13
Salt Lake City	May-14
San Antonio	May-14
San Diego	May-13
San Francisco	Jul-12
Seattle	Aug-11
St Louis	Oct-14
Tampa	Apr-14

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