Do Ride-sharing Services Affect Traffic Congestion? An Empirical Study of Uber Entry

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Sharing economy platform, which leverages information technology (IT) to re-distribute unused or under-utilized assets to people who are willing to pay for the services, has received tremendous attention in the last few years. Its creative business models have disrupted many traditional industries (e.g., transportation, hotel) by fundamentally changing the mechanism to match demand with supply in real time. In this research, we investigate how Uber, a peer-to-peer mobile ride-sharing platform, affects traffic congestion and environment (carbon emissions) in the urban areas of the United States. Leveraging a unique data set combining data from Uber and the Urban Mobility Report, we examine whether the entry of Uber car services affects traffic congestion using a difference-in-difference framework. Our findings provide empirical evidence that ride-sharing services such as Uber significantly decrease the traffic congestion after entering an urban area. We perform further analysis including the use of instrumental variables, alternative measures, a relative time model using more granular data to assess the robustness of the results. A few plausible underlining mechanisms are discussed to help explain our findings.

Key words: sharing economy, ride-sharing services, digital platforms, traffic congestion

1. Introduction

Platform-based sharing economy, also referred to as collaborative consumption, gig economy or collaborative economy, has received tremendous attention in recent years. This concept was first proposed when Benkler (2002) published a paper suggesting that we share goods in economic process. Many studies subsequently explored the potential of the sharing economy (Avital et al. 2014, Botsman and Rogers 2011, Felländer et al. 2015, Sundararajan 2013, 2014). In 2011, TIME magazine named sharing economy one of the "ten ideas that will change the world". According to Price Waterhouse Coopers, five key sharing sectors (P2P finance, online staffing, P2P accommodation, car sharing and music/video streaming) have the potential to increase global revenues from around \$15 billion to around \$335 billion by 2025.[1]

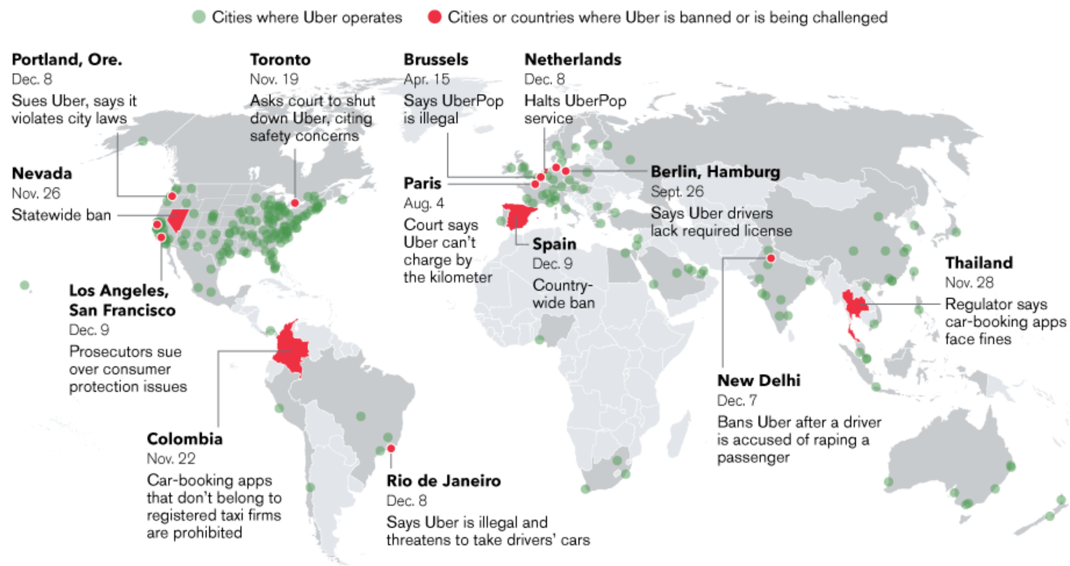
Although there are many success stories regarding the sharing platforms in recent years, it is not clear how such platforms could impact the economy and society. In fact, the disruptive force of the sharing platforms has raised challenges for many incumbent industries as well as policy makers. Traditional mature industries such as the hotel and the automotive industries were affected because consumers now have convenient and cost efficient access to resources without the financial, emotional, or social burdens of ownership (Bardhi and Eckhardt 2015). Sharing economy also raised debates on regulatory and safety concerns (Feeney and companies Uber 2015, Malhotra and Van Alstyne 2014). As a result, some traditional companies have tried to lobby the politicians to regulate the growth of the sharing economy (Wallsten 2015).

As one of the most successful examples of the sharing economy, Uber has raised the most heated debates. Advocates view Uber services as an important complement to the existing modes of urban transportation. Others, however, criticize that sharing economy platforms often restructure the nature of employment and circumvent regulations in order to maximize company benefits. Uber, for instance, hires drivers as "independent contractors" as opposed to "employees". Therefore, their basic rights as workers are not guaranteed. Figure 1 shows a map of the worldwide cities where Uber operates and where it is banned or is being challenged.

In recent years, researchers have started to examine the effects of the sharing economy (particularly Uber) on social issues. A few studies in this area centered around traffic and transportation

[1] `http://www.pwc.co.uk/issues/megatrends/collisions/sharingeconomy/the-sharing-economy-sizing-the-revenue-opportunity.html`

Figure 1 Where Uber operates, and where it's been shut down.



Note. Sources: Uber, Bloomberg reporting.

considering Uber is using technology to improve the access and reliability to transportation. For example, Greenwood and Wattal (2015) found that Uber decreases the rate of alcohol related motor vehicle homicides. Rayle et al. (2014) used an intercept survey to study the usage and impacts of ride sharing, and found that it actually fulfills an unserved demand of convenient, point-to-point urban travel. Wallsten (2015) reveals that Uber's popularity is associated with the decrease of consumer complaints about taxi in some cities. A recent report by American Public Transportation Association[2] shows that share modes (car sharing, ride sharing) complement public transit, decrease car ownership and enhance urban mobility. An important question is does Uber really have an impact on the traffic congestion in urban areas? There are two countervailing perspectives (Alexander and González 2015) to this question. On one hand, by providing more convenient, less expensive ride-sharing services, Uber diverts non-driving trips like walking, transit, or cycling to driving mode. Hence, Uber could induce additional traffic volume and increase traffic congestion. On the other hand, as a ride-sharing service provider, Uber has the potential to reduce traffic by diverting trips otherwise made in private, single occupancy cars or taxis.

[2] `http://www.apta.com/resources/reportsandpublications/Documents/APTA-Shared-Mobility.pdf`

A few studies have looked into this issue, but the findings are inconclusive. One study from New York Times estimated that Uber vehicles contribute to about 10 percent of traffic in Manhattan during evening rush hours, but contended that it's hard to measure the causal impact of Uber on the overall traffic increase.[3] In a separate study, the Office of the Mayor in New York City released a report in January 2016, highlighting that the city mayor's contention that Uber vehicles and other ride-sharing services had worsened traffic in Manhattan is unfounded.[4] In summary, there is limited empirical evidence to validate arguments on either side.

In this study, we use a natural experiment approach to empirically examine the impact of Uber on traffic congestion in different urban areas of the United States. This research design offers us an important advantage: Since the time of Uber entry into various urban areas is different, we can use a difference-in-difference method to investigate whether the traffic congestion before and after Uber entry is different across different urban areas. Our data come from multiple sources. First, the urban mobility report contains different elements of congestion data for each of the 101 urban areas in the United States from 1982 to 2014. Additionally, we conduct comprehensive due diligence research and collect the entry time of Uber into an urban area from Uber's official web site. In order to control the possible effects of other variables, we also collected data on fuel cost, socio-economic characteristics of the urban areas, characteristics of road transport systems from United States Census Bureau and Bureau of Economic Analysis. After integrating data from these sources, we construct an urban area-year level panel data set that includes 957 observations spanning 11 years over 87 urban areas in the United States.

We find empirical evidence that the entry of Uber actually leads to a significant decrease in traffic congestion and carbon dioxide emissions in the urban areas of the United States. Moreover, these results are consistent for different measures of the traffic congestion. To assess the robustness of the results, we perform further analysis including the use of instrumental variables (IV), alternative

[3] `http://www.nytimes.com/2015/07/28/upshot/blame-uber-for-congestion-in-manhattan-not-so-fast.html`

[4] `http://www.nytimes.com/2016/01/16/nyregion/uber-not-to-blame-for-rise-in-manhattan-traffic-congestion-report-says.html`

measures, and more granular data. We provide a few plausible underlining mechanisms to help explain our findings. This paper contributes to the existing literature by providing additional empirical evidence of the social benefits associated with the sharing economy. Additionally, it offers valuable insights about the broader impact of ride-sharing services on the transportation industry.

The rest of the paper is organized as follows. Section 2 reviews relevant literature on the digital infrastructure and platforms. Section 3 describe in detail the data and our econometric specifications. Section 4 presents our findings as well as additional robustness checks. In Section 5, we discuss our results and provide a few underlining mechanisms to explain the results. Section 6 concludes and provides directions for future research.

2. Literature Review

Digital infrastructure and platforms bring together people, information, and technology to support business practices, social and economic activities, research, and collective action in civic matters (Adner and Kapoor 2010, Au and Kauffman 2008, Constantinides and Barrett 2014, Tilson et al. 2010). Research examining the transformative role of digital infrastructure and platforms abound. Some representative work include Seamans and Zhu (2013), who study the impact of Craigslist on the classified-ad rates, subscription prices, circulation in the local U.S. newspapers. Chan and Ghose (2013) investigate whether the entry of Craigslist increases the prevalence of HIV. In a separate study, Greenwood and Agarwal (2015) also find a significant increase in the HIV incidence after the introduction of the online matching platform Craigslist. Bapna et al. (2016) estimate the causal effect of the anonymity feature on matching outcomes on online dating web sites. They find that anonymous users, who lose the ability to leave a weak signal, end up having fewer matches as compared to their non-anonymous counterparts.

Crowdfunding is another topic that has received extensive attention in platform research. Wei and Lin (2015) evaluate two market mechanisms (auctions and posted prices) in online peer-to-peer lending based on market participants, transaction outcomes, and social welfare. There is also empirical evidence that home bias exists in online crowdfunding marketplaces for financial products

(Lin and Viswanathan 2015). Lin et al. (2013) find that the online friendships of borrowers act as signals of credit quality in the context of Prosper.com, the largest online P2P lending marketplace. Burtch et al. (2013) examine both the antecedents and the consequences of the contribution process in a crowd-funding platform.

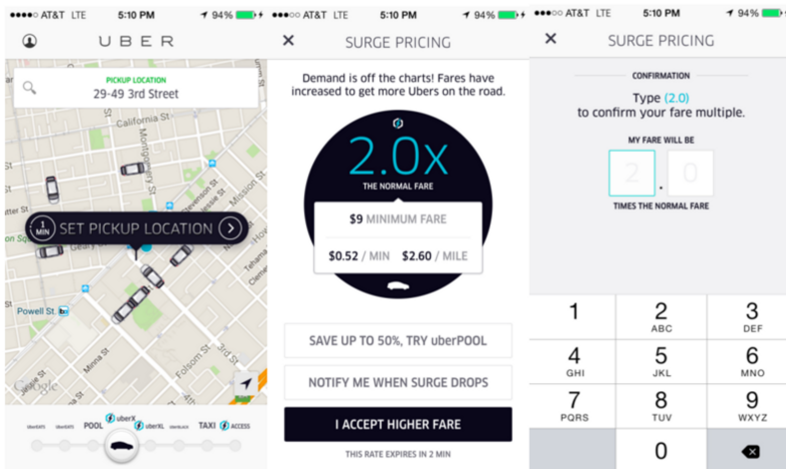
Another stream of research on digital platforms examine their impacts on traditional industries such as the hotel and the transportation industries. Zervas et al. (2016) estimate that each 10% increase in *Airbnb* supply results in a 0.37% decrease in monthly hotel room revenue. Wallsten (2015) explores the competitive effects of ride-sharing on the taxi industry and finds that *Uber*'s popularity decreases the consumer complaints per trip about taxi in New York City and decreases specific types of complaints about taxi in Chicago.

On-demand, real-time ride-sharing services (e.g., Uber) have similarities with traditional share modes such as car sharing, but offer some unique characteristics. Alexander and González (2015) explored how ride-sharing affects traffic congestion using mobile phone data and found that under moderate to high adoption rate scenarios, ride-sharing would likely have noticeable effects in reducing congested travel times. Fellows and Pitfield (2000) found that car sharing benefits individuals by halving journey costs and benefits the whole economy by reducing vehicle kilometers, increasing average speeds and savings in fuel, accidents and emissions. Jacobson and King (2009) investigated the potential fuel savings in the US when traditional ride-sharing policy was announced and found that if 10% cars were to have more than one passenger, it could reduce 5.4% annual fuel consumption. Caulfield (2009) estimated the environmental benefits of traditional ride-sharing in Dublin and found that 12,674t of CO2 emissions were saved by individual ride-sharing.

3. Data and Methods

Our research setting is the Uber platform, the most successful ride-sharing digital platform in the context of the sharing economy. Officially launched in San Francisco in 2011, Uber has grown from a small start-up company in Silicon Valley to an international corporation with billions of dollars of funding. By April 12, 2016, Uber was available in over 60 countries and 404 cities worldwide.

Figure 2 Uber's surge pricing in action



Note. Photo: Uber

Uber's two-sided platform business model has made it possible for riders to simply tap their smartphones and have a cab arrive at their location in the minimum possible time. When a rider opens the Uber app, she chooses a ride type (e.g., UberX, UberBlack, UberSUV) and set her location. The Uber platform automatically assign a driver to the rider request and then the driver on the other side of the platform respond to the request. The rider will see the driver's name, picture and vehicle details, and can track the estimated time of arrival on the map. The pay process is "no cash, no tip and no hassle". If the current time period is peak demand time, the customer will face surge pricing. But they are notified before making the decision, as shown in the Figure2. After a ride is completed, the rider can rate the driver and provide anonymous feedback about her trip experience.

3.1. Data

Our data come from a few sources. We retrieved the congestion data from the Urban Mobility Report (UMR), provided by the Texas A&M Transportation Institute (TTI). The Urban Mobility Report contains the urban mobility and congestion statistics for each of the 101 urban areas in the U.S. from 1982 to 2014. This report is acknowledged as the authoritative source of information about traffic congestion and is widely used in the transportation literature. For each of the urban areas in the UMR, we searched the official Uber newsroom as well as the major news media to find out if and when Uber arrived in an urban area.[5] Fourteen (out of 101) urban areas have Uber services according to the official Uber web site, but we could not verify the exact Uber entry time (year and month) into these areas. Hence these areas are not included in our sample. In addition, given that the earliest Uber entry time (into San Francisco) is 2011, we choose the time window between 2004 and 2014 to balance the number of time periods before and after the Uber entry. Our final panel data comprises 957 observations spanning 11 years over 87 urban areas in the United States.

3.2. Dependent variables

Our target variable is the traffic congestion. We adopted four important indicators from the UMR to measure congestion. The first measure is the *Travel Time Index (TTI)*, which has been used in previous studies (Bertini 2006, Hagler and Todorovich 2009, Litman 2007, Mehran and Nakamura 2009, Sweet and Chen 2011, Zhang 2011). TTI refers to the ratio of the travel time in the peak period to that at free-flow conditions. A value of $TTI = 1.20$, for example, indicates that a 20-minute free-flow trip requires 24 minutes during the peak period.

The second variable to measure congestion is the *Commuter Stress Index (CSI)*. CSI refers to the travel time index calculated for only the peak direction in each peak period. The CSI is believed to be more indicative of the work trip experienced by each commuter on a daily basis.[6] It is worth noting that both the TTI and the CSI are travel indices and do not represent the actual time of delay due to congestion.

In order to capture that, we adopted the *delay time* and the *delay cost*. Delay time is the amount of the extra time spent on traveling due to congestion. The delay (congestion) cost refers to the value of the travel delay, taking into account both the cost of delayed time and the cost of wasted fuel. Finally, a direct consequence of traffic congestion is the increased level of carbon dioxide

[5] There is a slight difference between an urban and a metropolitan area. The urban mobility report is the finest official data we can get to measure traffic at the urban area.

[6] David Schrank, Bill Eisele, Tim Lomax, Jim Bak, "2015 Urban Mobility Scorecard", Texas Transportation Institute, `http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-scorecard-2015.pdf`.

emissions from vehicles. In order to analyze the potential environment effect, we use excess fuel consumption due to congestion to proxy for carbon dioxide emissions. For delay time, delay cost, and the excess fuel consumption, we adopted both the annual total measurement as well as the per auto commuter measurements.

Table 1 provides the summary statistics of the eight variables we discussed to measure various aspects of traffic congestion. Since these variables exhibit significant skewness, we use the log transformations in our later analysis.

Table 1 **Definition and Summary Statistics of Eight Performance Measures of Traffic Congestion**

Variable	Definition	Mean	Std. Dev.	Min	Max
TTI	Travel Time Index	1.20	0.08	1.07	1.45
CSI	Commuter Stress Index	1.25	0.10	1.07	1.64
DT	Annual hours of total delay (in thousands)	61,401	99,994	2,035	630,722
DTPA	Annual hours of delay per auto commuter	41	12	12	86
DC	Annual congestion cost (million dollars)	1,553	2,492	70	16,346
DCPA	Annual congestion cost per auto commuter($)	1,000	293	323	2,069
EF	Annual excess fuel consumed due to congestion (Total gallons in thousand)	27,462	41,444	1,106	296,701
EFPA	Excess Fuel (gallons per auto commuter)	18	5	5	35

3.3. Control Variables

We control for the effects of a number of variables including the lane miles of road and the amount of travelers. These variables have been identified in the previous literature to influence traffic congestion. Additionally, we control for the variables that may play a role in Uber's decision to enter different urban areas/cities. These variables include the population size and the socio-economic status (such as GDP, median income) of an urban area. Table 2 describes the control variables as well as the summary statistics of these variables.

Table 2 Definition and Summary Statistics of Control Variables

Variable	Definition	Mean	Std. Dev.	Min	Max
GDP	GDP in dollars	119,242	181,231	3,641	1,423,173
POP	Population	1,821	2,619	105	19,040
Income	Median Income	48,444	8,163	32,875	76,165
FDVMT	Freeway Daily Vehicle Miles of Travel (000)	16,344	21,506	480	139,275
ASDVMT	Arterial Street Daily Vehicle Miles of Travel (000)	16,104	20,184	988	126,010
Commuters	Number of auto commuters (000)	825	976	51	5,928
Diesel Cost	Average Gasoline Cost ($/gallon)	3.25	0.69	1.77	4.91
Gasoline Cost	Average Diesel Cost ($/gallon)	2.92	0.56	1.77	4.35

3.4. Empirical Model and Specification

As discussed earlier, Uber arrives in various urban areas at different points of time. This allows us to use an exogenous entry model for identification. Specifically, by repeatedly observing the congestion level in each urban area over time, we could employ a difference-in-difference framework to examine the difference in congestion before and after Uber entry across multiple areas. Difference-in-Difference estimation has become an increasingly popular way to estimate causal relationships (Bertrand et al. 2002). It is appropriate when one wants to compare the difference in outcomes after and before the intervention for the treated groups to the same difference for the un-treated groups. In order to control the ex-ante differences between the heterogeneous urban areas, we include area fixed effects in our model. Our complete model specification is given by:

$$Congestion_{it} = \alpha + \delta \times Uber\ Entry_{it} + \lambda \times Controls_{it} + \theta_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where $Controls_{it}$ represent the control variables for urban area i in year t, α is the grand mean congestion level. $Uber\ Entry_{it}$ is a dummy variable. It equals to 1 if urban area i has Uber service in year t, and zero otherwise. The parameters δ and λ are coefficients; θ_i and γ_t represent the urban area fixed effect and the time fixed effect. Fixed effects capture not only non-time varying factors but also allow the error term to be arbitrarily correlated with other explanatory variables, thus making the model estimation robust (Angrist and Pischke 2008). The error term is ε_{it}. We use robust standard errors clustered at the urban areas to deal with potential issues of heteroscedasticity.

4. Results

Tables 3 and 4 present the coefficient estimates of Equation (1) with each column using a different measure of traffic congestion. It can be seen that the effect of Uber entry is pretty consistent. The estimate of the effect (except on TTI and Excess fuel per auto) is significant and negative for all measures of congestion (except for excess fuel per auto). Note that the estimate of Uber entry on TTI is negative and the p value of the estimate is 0.12, hence marginally significant given our sample size is only 957 with two way fixed effects. The estimate of Uber entry on Excess fuel per auto is insignificant (p = 0.615). Overall we find empirical evidence that Uber significantly decreases traffic congestion in the urban areas of the U.S. It is worth noting that as the median income in an urban area increases, the traffic tends to get worse. This is consistent with the existing literature that traffic conditions in a city are usually associated with the overall economic activities.

4.1. Instrumental Variables

In order to address the issue of endogeneity, we identified two instrumental variables (IV) to further assess the causal relationship between Uber and the traffic congestion. The first instrumental variable we used is the unemployment rate. From the United States Bureau of Labor Statistics, we collected data on the unemployment rate of 87 urban areas from 2004 to 2014. This variable serves as a valid instrument because it is not likely to be correlated with the traffic congestion, but is an important factor for Uber executives to consider when deciding a go-to market strategy. A unique feature of Uber's business model is that it provides flexible job opportunities that attract

Table 3 Estimation Results of Uber Entry on Traffic Congestion

	(1) TTI	(2) CSI	(3) DC	(4) DCPA
Uber Entry	-0.00237^{+}	-0.00377***	-0.0121**	-27.32***
	(0.00151)	(0.00139)	(0.00600)	(7.271)
GDP	0.000364	0.000457	0.00391	3.337
	(0.000776)	(0.000697)	(0.00297)	(3.424)
Income	0.0515***	0.0580***	0.255***	218.7***
	(0.0133)	(0.0139)	(0.0696)	(59.51)
Population	-0.0230	-0.0274	0.117	9.995
	(0.0390)	(0.0391)	(0.141)	(188.5)
Commuters	-0.0316	-0.0325	0.603***	739.8***
	(0.0400)	(0.0408)	(0.153)	(194.6)
Gasoline Cost	-0.00335	-0.00919	-0.0505	-48.53
	(0.0132)	(0.0132)	(0.0573)	(54.28)
Diesel Cost	0.0169	0.0138	0.112	163.9**
	(0.0154)	(0.0157)	(0.0889)	(78.98)
FDVMT	0.00828	0.00780	0.0748	55.72
	(0.0138)	(0.0148)	(0.0659)	(69.97)
ASDVMT	0.0185**	0.0130	0.0733*	86.16*
	(0.00877)	(0.00841)	(0.0436)	(45.61)
Constant	0.745***	0.815***	-1.985	-7,355***
	(0.276)	(0.286)	(1.312)	(1,265)
Observations	957	957	957	957
Number of urban areas	87	87	87	87
R-squared	0.241	0.262	0.478	0.538

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

independent contractors to participate in the labor market. Hence, Uber may be well received in areas with higher unemployment rates.

Following Angrist and Pischke (2008), we estimate the IV model with the 2SLS approach. Specially, we estimate the probability that Uber enters an urban area using the standard linear probability approach and then included it in the second stage estimation. Table 5 reports the results of this analysis, providing further empirical evidence of our main results. We report the first stage results and the fit statistics in Table 6. It can be seen that there is a significant correlation between the IV (unemployment rate) and the Uber entry time ($p = 0.018$). Additionally, the first stage F statistics are all significant. Both the CraggDonald Wald F statistics and the Kleibergen-Paap Wald rk F statistic pass the critical value suggested by Stock and Yogo (2005), alleviating the weak instrument concern.

We repeated the same analysis using another instrumental variable: percent of population ages 65 and above. The percent of senior citizens is not expected to be correlated with traffic congestion,

Table 4 Estimation Results of Uber Entry on Traffic Congestion (cont'd)

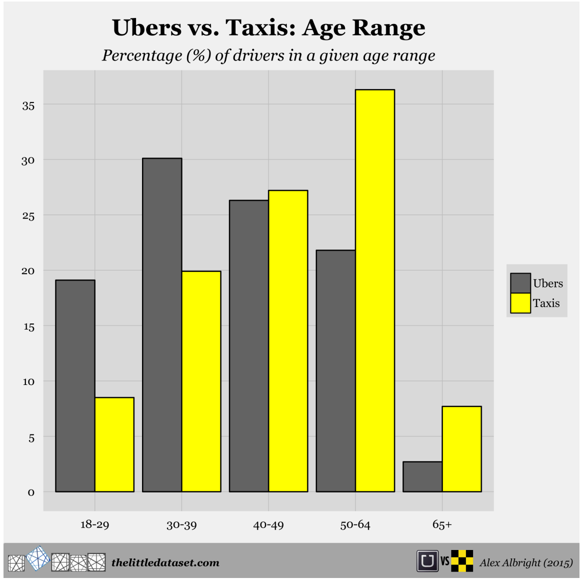
	(5) DT	(6) DTPA	(7) EF	(8) EFPA
Uber Entry	-0.0121**	-0.491*	-0.0121**	0.210
	(0.00599)	(0.252)	(0.00599)	(0.133)
GDP	0.00388	0.127	0.00389	0.0652
	(0.00297)	(0.145)	(0.00297)	(0.0820)
Income	0.256***	9.674***	0.256***	4.746***
	(0.0692)	(2.416)	(0.0692)	(1.166)
Population	0.118	-5.202	0.118	3.555
	(0.141)	(7.546)	(0.141)	(4.039)
Commuters	0.599***	-6.314	0.599***	8.972**
	(0.153)	(7.733)	(0.153)	(4.112)
Gasoline Cost	-0.0499	-1.067	-0.0498	0.316
	(0.0573)	(2.272)	(0.0573)	(1.148)
Diesel Cost	0.113	5.160*	0.113	1.991
	(0.0891)	(2.621)	(0.0891)	(1.285)
FDVMT	0.0759	2.361	0.0760	-0.329
	(0.0660)	(2.561)	(0.0660)	(1.136)
ASDVMT	0.0742*	3.202*	0.0742*	1.181
	(0.0436)	(1.710)	(0.0436)	(0.821)
Constant	1.534	-42.70	0.784	-124.0***
	(1.307)	(45.01)	(1.307)	(21.82)
Observations	957	957	957	957
Number of urban areas	87	87	87	87
R-squared	0.687	0.292	0.687	0.648

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

but may influence the decision by *Uber* executives to not enter certain urban areas. Previous research (e.g., Warschauer 2004) have shown that elderly people are more likely to suffer digital inequalities. Since Uber represents a new phenomenon/trend and is more likely to be adopted by tech-savvy young generations, it is more (less) likely to offer services in urban areas with a higher (lower) percentage of young people. Recent statistics of Uber users (both drivers and passengers) provide anecdotal evidence on our reasoning. From Figure 3, we see that the medium age of Uber drivers is much younger than that of Taxi drivers. As for passengers, only two percent of Uber users are over 55 years (Figure 4).

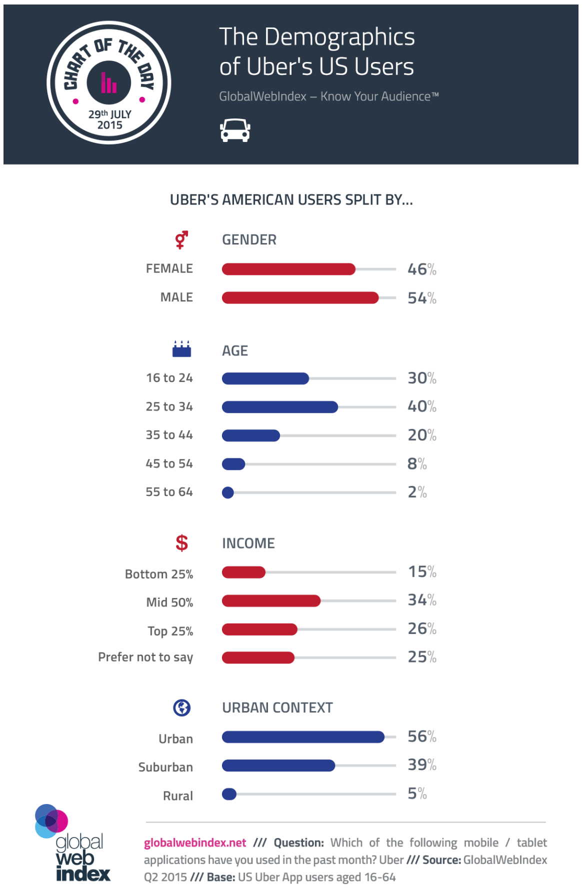
The results of the 2SLS analysis using the percent of population ages 65 and over are presented in Table 7. The first stage results and the F statistics are reported in Table 8. These results further strengthen the evidence that Uber significantly reduces traffic congestion in urban areas.

Figure 3 Age Range of Uber drivers vs. Taxis drivers



Note. Data source: Hall and Krueger(2015)

Figure 4 Uber's surge pricing in action



Note. Source: GlobalWebIndex Q2 2015

Table 5 2SLS Estimation Results Using Unemployment Rate as the IV

	(1) TTI	(2) CSI	(3) DC	(4) DCPA	(5) DT	(6) DTPA	(7) EF	(8) EFPA
Uber Entry	-0.153**	-0.168**	-0.745**	-821.5**	-0.744**	-30.88**	-0.745**	-12.75**
	(0.0677)	(0.0734)	(0.327)	(346.1)	(0.327)	(13.37)	(0.327)	(5.797)
Population	0.364*	0.396*	2.004**	2,055**	73.04*	2.004**	36.93**	
	(0.202)	(0.220)	(0.978)	(1,047)	(0.977)	(39.98)	(0.977)	(17.26)
GDP	-0.000818	-0.000838	-0.00186	-2.917	-0.00188	-0.113	-0.00188	-0.0369
	(0.00265)	(0.00289)	(0.0129)	(14.09)	(0.0129)	(0.528)	(0.0129)	(0.221)
Income	0.0426	0.0483	0.212	172.0	0.213	7.885	0.213	3.983
	(0.0315)	(0.0347)	(0.153)	(165.9)	(0.153)	(6.348)	(0.153)	(2.730)
Commuters	-0.374**	-0.408**	-1.070	-1,073	-1.072	-75.68**	-1.073	-20.62
	(0.180)	(0.196)	(0.869)	(932.5)	(0.868)	(35.48)	(0.868)	(15.38)
Gasoline Cost	0.0267	0.0238	0.0964	110.7	0.0969	5.024	0.0970	2.914
	(0.0568)	(0.0620)	(0.279)	(300.6)	(0.279)	(11.50)	(0.279)	(4.945)
Diesel Cost	-0.0209	-0.0276	-0.0723	-35.80	-0.0712	-2.480	-0.0713	-1.268
	(0.0478)	(0.0515)	(0.235)	(249.6)	(0.234)	(9.567)	(0.234)	(4.185)
FDVMT	-0.0335	-0.0380	-0.129	-165.3	-0.128	-6.096	-0.128	-3.936
	(0.0342)	(0.0372)	(0.164)	(175.9)	(0.164)	(6.782)	(0.164)	(2.934)
ASDVMT	0.0505*	0.0480	0.229*	255.4*	0.230*	9.676*	0.230*	3.942*
	(0.0275)	(0.0299)	(0.134)	(143.8)	(0.134)	(5.512)	(0.134)	(2.386)
Observations	957	957	957	957	957	957	957	957
Number of urban area	87	87	87	87	87	87	87	87
R-squared	-9.152	-10.210	-6.134	-7.092	-3.281	-11.107	-3.283	-3.545

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

Table 6 IV First Stage Analysis (Unemployment Rate)

	Uber Entry Dummy
Unemployment Rate	0.093*(0.050)
Population	2.58***(0.74)
GDP	-0.0077(0.017)
Income	0.0076 (0.210)
Commuters	-2.29***(0.73)
Gasoline Cost	0.23 (0.36)
Diesel Cost	-0.19 (0.30)
FDVMT	-0.27*(0.18)
ASDVMT	0.21 (0.16)
Observations	957
Number of urban areas	87
F statistics	3.37*

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

4.2. Alternative Measure for Uber Entry

So far, we have used Uber entry time to proxy for the implementation of Uber service. This approach has limitations. Specifically, after *Uber* service enters an urban area, it takes time for people to accept and get accustomed to this new service. Therefore, Uber entry may not represent

Table 7 2SLS Estimation Results Using Percent of Olds as the IV

	(1) TTI	(2) CSI	(3) DC	(4) DCPA	(5) DT	(6) DTPA	(7) EF	(8) EFPA
Uber Entry	-0.0182*	-0.0155+	-0.194**	-215.5***	-0.191**	-2.106	-0.191**	1.571*
	(0.00988)	(0.00998)	(0.0827)	(70.69)	(0.0819)	(1.527)	(0.0819)	(0.862)
Population	0.0178	0.00274	0.587**	494.6*	0.578**	-1.044	0.578**	0.0496
	(0.0386)	(0.0384)	(0.265)	(262.2)	(0.263)	(6.104)	(0.263)	(3.433)
GDP	0.000240	0.000365	0.00247	1.854	0.00248	0.114	0.00248	0.0759
	(0.000550)	(0.000498)	(0.00342)	(3.612)	(0.00336)	(0.0889)	(0.00336)	(0.0675)
Income	0.0505***	0.0573***	0.245***	207.7***	0.245***	9.579***	0.245***	4.826***
	(0.00858)	(0.00857)	(0.0513)	(50.56)	(0.0506)	(1.476)	(0.0506)	(0.783)
Commuters	-0.0678*	-0.0593*	0.187	310.2	0.192	-10.00*	0.192	12.08***
	(0.0348)	(0.0345)	(0.245)	(246.1)	(0.242)	(5.755)	(0.242)	(3.234)
Gasoline Cost	-0.000179	-0.00685	0.0661	-10.81	-0.0142	-0.743	-0.0140	0.0435
	(0.0128)	(0.0130)	(0.0872)	(88.46)	(0.0863)	(2.171)	(0.0863)	(1.144)
Diesel Cost	0.0129	0.0108	0.0661	116.6	0.0681	4.754**	0.0680	2.333*
	(0.0128)	(0.0128)	(0.0821)	(77.63)	(0.0813)	(2.170)	(0.0813)	(1.202)
FDVMT	0.00387	0.00454	0.0241	3.346	0.0263	1.911	0.0264	0.0501
	(0.00804)	(0.00809)	(0.0528)	(50.91)	(0.0523)	(1.416)	(0.0523)	(0.720)
ASDVMT	0.0219***	0.0155***	0.112***	126.3***	0.112***	3.546***	0.112***	0.891*
	(0.00609)	(0.00584)	(0.0435)	(41.65)	(0.0430)	(1.036)	(0.0430)	(0.521)
Observations	957	957	957	957	957	957	957	957
Number of urban area	87	87	87	87	87	87	87	87
R-squared	0.137	0.209	0.069	0.110	0.451	0.260	0.451	0.601

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

Table 8 IV First Stage Analysis (percent of olds)

	Uber Entry Dummy
Percent of olds	-0.00017**(0.00004)
Population	1.994***(0.752)
GDP	-0.008 (0.018)
Income	0.031 (0.198)
Commuters	-1.921***(0.730)
Gasoline Cost	0.065 (0.359)
Diesel Cost	-0.237 (0.300)
FDVMT	-0.320*(0.180)
ASDVMT	0.198 (0.152)
Observations	957
Number of urban areas	87
F statistics	13.50***

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

the actual usage rate, and there may be a time lag between Uber entry and its impact on the traffic congestion. In order to alleviate this concern, we use an alternative measure of *Uber Entry* in urban areas: the number of Uber searches in an urban area on *Google Trends*. *Google Trends* is a publicly available web application based on Google Search. It provides us an index of the popularity of ride-sharing in a certain geographic region. Google Trends have been previously demonstrated to track economic activities (retail sales, automotive sales, home sales, and travel) in real time (Choi and Varian 2012). Wu and Brynjolfsson (2013) find that Google Trends are better in predicting housing sales and prices than traditional indicators.

We used the *Google Trends* search history of the keyword combination "Uber" + "name of the urban area" to measure the popularity and the usage level of *Uber* in an urban area. It's reasonable to assume that when a person search "Uber New York", she is likely to be interested in the Uber service in the New York City. Figure 5 plots the search history of Uber service in three cities: San Francisco, Phoenix, and Austin along with the corresponding actual Uber entry time in each city. We observe that even though Uber entered San Francisco in June 2011, it only began to become popular after some time. Similarly, Uber entered Phoenix in October 2012, but began to attract public attention around 2014. The correlation between Uber entry time and the search volume on Google is positive and significant.

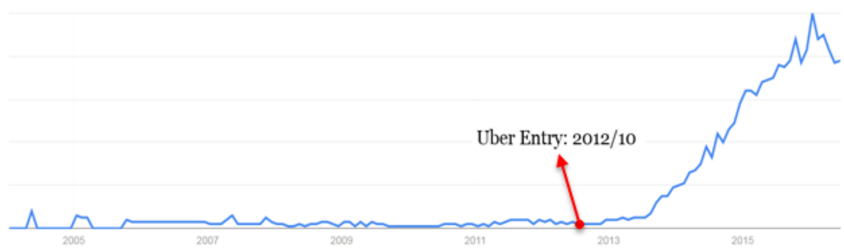
There is, however, a potential issue with the search volume on Google trends. Before Uber actually entered an urban area, the search volume is generally not zero in most urban areas. The non-zero search volume could represent some expectations and curiosity but not the actual Uber usage. We address this problem by multiplying it with the Uber entry dummy variable as a new variable: *Uber usage*. Table 9 presents the results of our analysis using Uber usage. Once again, we find that our estimation results are robust to this alternative measure.

4.3. Monthly Level Analysis

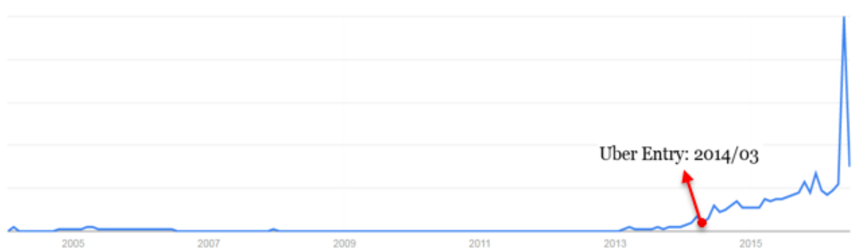
4.3.1. DID Analysis To further test the robustness of our model, we perform monthly level analysis. We obtained the monthly traffic data from the Federal Highway Administration (FHWA). This data set is slightly different from the data set we used for our main analysis. It is monthly level data ranging from January 2012 to December 2015. The unit of geographic region is Metropolitan Statistical Area (MSA) instead of urban area. Delay cost, Delay time and excess fuel consumption are also not available in the monthly level data. As a result, we use TTI and congested hours

Figure 5 Time trends of "Uber" + sample urban areas on Google Trends

Search volume of "Uber **San Francisco**" over time trends



Search volume of "Uber **Phoenix**" over time trends



Search volume of "Uber **Austin**" over time trends

Note. Source: Google Trends

(CH) as dependent variables in our monthly level data analysis. The summary statistics of the two variables are shown in Table 10.

We adopt the same DID model and apply it on this new monthly data. Since traffic patterns exhibit strong seasonal fluctuations, we include the seasonal fixed effect in our model. The results of the monthly level analysis are shown in Table 11. We can see that the coefficients of Uber entry are negative and significant for both dependent variables. Another interesting finding is that the diversity of Uber service has significant and negative effect on congestion. The diversity of Uber service refers to the number of car types that is available to a customer (Figure 6(a)) when she opens the app in a geographical area; different car type services come with different fares (Figure 6(b)). We believe that the diversity and multiplicity of Uber services will stimulate more Uber

Table 9 Estimation Results Using Alternative Measure

	(1) TTI	(2) CSI	(3) DC	(4) DCPA	(5) DT	(6) DTPA	(7) EF	(8) EFPA
Uber Use	-0.000421^{+}	-0.000626**	-0.00231**	-4.817***	-0.00231**	-0.0862*	-0.00231**	0.0283
	(0.000258)	(0.000243)	(0.00106)	(1.286)	(0.00106)	(0.0434)	(0.00106)	(0.0225)
GDP	0.000373	0.000472	0.00395	3.440	0.00393	0.129	0.00393	0.0642
	(0.000771)	(0.000691)	(0.00296)	(3.373)	(0.00295)	(0.144)	(0.00295)	(0.0822)
Income	0.0516***	0.0581***	0.256***	219.7***	0.256***	9.691***	0.256***	4.737***
	(0.0133)	(0.0139)	(0.0695)	(59.33)	(0.0691)	(2.415)	(0.0691)	(1.167)
Population	-0.0221	-0.0267	0.125	19.63	0.126	-5.035	0.126	3.624
	(0.0391)	(0.0394)	(0.141)	(189.0)	(0.141)	(7.581)	(0.141)	(4.049)
Commuters	-0.0323	-0.0331	0.597***	731.8***	0.593***	-6.453	0.593***	8.908**
	(0.0401)	(0.0411)	(0.153)	(194.7)	(0.153)	(7.763)	(0.153)	(4.113)
Gasoline Cost	-0.00342	-0.00934	-0.0507	-49.30	-0.0501	-1.081	-0.0500	0.331
	(0.0132)	(0.0132)	(0.0573)	(54.43)	(0.0573)	(2.275)	(0.0573)	(1.147)
Diesel Cost	0.0167	0.0136	0.111	161.9**	0.112	5.125*	0.112	1.990
	(0.0153)	(0.0157)	(0.0886)	(78.39)	(0.0888)	(2.612)	(0.0888)	(1.282)
FDVMT	0.00798	0.00742	0.0729	52.32	0.0740	2.300	0.0741	-0.322
	(0.0138)	(0.0148)	(0.0658)	(69.84)	(0.0660)	(2.566)	(0.0660)	(1.140)
ASDVMT	0.0186**	0.0131	0.0742*	87.67*	0.0751*	3.229*	0.0751*	1.182
	(0.00883)	(0.00845)	(0.0438)	(45.90)	(0.0438)	(1.717)	(0.0438)	(0.823)
Constant	0.744***	0.814***	-1.991	-7,363***	1.528	-42.85	0.778	-124.1***
	(0.276)	(0.286)	(1.309)	(1,261)	(1.304)	(44.96)	(1.305)	(21.82)
Observations	957	957	957	957	957	957	957	957
Number of id	87	87	87	87	87	87	87	87
R-squared	0.242	0.262	0.479	0.539	0.687	0.293	0.687	0.647

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

Table 10 Definition and Summary Statistics of DV in Monthly Level Data

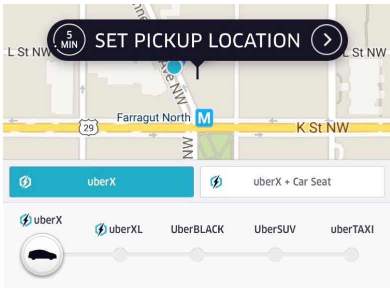
Dependent Variable	Definition	Mean	Std. Dev	Min	Max
TTI(Travel Time Index)	Peak period vs. offpeak travel times	1.22	0.13	1.02	1.8
CH (Congested Hours)	Average duration of daily congestion	4.12	1.9	0.33	12.05

usage, thus reducing congestion. Table 11 shows that as the diversity of Uber service increases, both TTI and CH decrease.

Additionally, we conducted IV analysis (using the unemployment rate) on monthly level data.[7] The results are presented in Table 12 and Table 13. The coefficients and the F statistics are consistent with our annual level analysis.

4.3.2. Relative Time Analysis The richness of the monthly level data allows us to conduct a relative time analysis. The advantage of the relative time model over DID is that it helps evaluate

[7] Data of the percent of population ages 65 and over is not available at the monthly level.



(a) Uber pickup location screenshot

	For Hire	uberX	uberXL	Black Car	SUV
Base Fare	\$1.99	\$1.35	\$3	\$7	\$14
Per Mile	\$1.99	\$1.35	\$2.75	\$3.75	\$4.20
Per Minute	\$0.25	\$0.24	\$0.30	\$0.35	\$0.40
Minimum Fare	\$6	\$4	\$6	\$12	\$20
Cancellation Fee	\$5	\$5	\$5	\$10	\$10

(b) Uber price comparison of different services

Figure 6 **Uber offers multiple services with varying price points**

Table 11 **Estimation Results of Impact of Uber Entry on Congestion using Monthly Level Data**

	(1) TTI	(2) CH
Uber Entry	-0.0111*	-0.275**
	(0.00587)	(0.121)
Diversity of Uber Service	-0.0624***	-1.096***
	(0.00453)	(0.0886)
GDP	-0.0592	-112.5
	(4.381)	(58.05)
Personal Income	9.57e-06*	8.68e-05
	(5.01e-06)	(7.24e-05)
Population	0.784	39.85***
	(0.704)	(11.65)
Constant	0.197	-30.12**
	(0.780)	(12.18)
MSA Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Seasonal Fixed Effect	Yes	Yes
Observations	2,352	2,352
R-squared	0.392	0.294
Number of MSA	49	49

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

the parallel trends assumption. According to Angrist and Pischke (2008), the key assumption of any DID model is the common trend assumption.

Our relative time model is specified in Equation (2). Following David (2003), Bapna et al. (2016), Chan and Ghose (2013), Greenwood and Wattal (2015), we include a series of time dummies ($j = t-6, ..., t+6$) that represent the chronological distance between an observation period, t, and the timing of treatment in MSA i. There are two advantages of this model: 1) it allows us to check the parallel trend assumption, and 2) it allows us to understand how long it takes for significant

Table 12 Estimation Results of IV with Unemployment using Monthly Level Data

	(1) TTI	(2) CH
Uber Entry	-0.0630***	-0.637^{+}
	(0.0240)	(0.459)
Diversity of Uber Service	-0.0630***	-1.100***
	(0.00498)	(0.0974)
GDP	3.485	-87.77**
	(2.351)	(40.51)
Personal Income	3.46e-07	2.25e-05
	(5.02e-06)	(9.38e-05)
Population	0.672	39.06***
	(0.601)	(11.27)
Observations	2,352	2,352
R-squared	0.309	0.279
Number of MSA	49	49

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

Table 13 IV First Stage Analysis (monthly data)

	Uber Entry Dummy
Unemployment Rate	0.0667 ***(0.327)
Unemployment Rate	0.0667 ***(0.327)
Control variables	Included
Time and MSA Fixed Effect	Yes
Observations	2352
Number of urban areas	49
F statistics	33.86***
Cragg-Donald Wald F statistic	32.84
Kleibergen-Paap Wald rk F statistic	33.86

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

effects to manifest.

$$Congestion_{it} = \alpha + \sum_{j=t-6}^{t+6} \delta_j \times (\mu_i \phi) + \lambda \times Controls_{it} + \theta_i + \gamma_t + \varepsilon_{it} \tag{2}$$

In this model, $Congestion_{it}$ represents the two dependent variables: TTI and CH. Since congested hours is not normally distributed, we log transformed this variable. The variable μ_i indicates whether or not Uber will ever enter area i, and ϕ is the relative time dummies. As before, there are two kinds of time fixed effects in our model: a year fixed effect and a seasonal fixed effect.

Table 14 presents the results of the relative time analysis. There are several interesting observations. First these results are consistent with the DID model. In addition, none of the pre-treatment periods is significant but all the post-treatment periods are significantly negative. This illustrates

Table 14 Estimation Results of Relative Time Model using Monthly Level Data

	(1) TTI	(2) CH
Rel Time$_{t-6}$	-0.00543	-0.0518
	(0.00712)	(0.0940)
Rel Time$_{t-5}$	0.00134	0.0191
	(0.00819)	(0.103)
Rel Time$_{t-4}$	-0.00437	-0.0852
	(0.00787)	(0.105)
Rel Time$_{t-3}$	-0.00670	0.0411
	(0.00627)	(0.108)
Rel Time$_{t-2}$	-0.00847	0.0444
	(0.00564)	(0.106)
Rel Time$_{t-1}$	Omitted	
Rel Time$_{t}$	-0.0115*	-0.137
	(0.00614)	(0.103)
Rel Time$_{t+1}$	-0.0208***	-0.278**
	(0.00597)	(0.116)
Rel Time$_{t+2}$	-0.0135**	-0.235**
	(0.00622)	(0.116)
Rel Time$_{t+3}$	-0.0166***	-0.348***
	(0.00594)	(0.107)
Rel Time$_{t+4}$	-0.0183***	-0.267***
	(0.00501)	(0.0971)
Rel Time$_{t+5}$	-0.0208***	-0.268***
	(0.00468)	(0.0938)
Rel Time$_{t+6}$	-0.0145**	-0.243***
	(0.00700)	(0.0885)
Diversity of Uber Service	-0.0630***	-1.103***
	(0.00453)	(0.0917)
GDP	-0.601	-126.5
	(4.474)	(60.89)
Personal Income	1.01e-05*	0.000114
	(5.28e-06)	(7.39e-05)
Population	0.732	39.06***
	(0.688)	(11.67)
Constant	0.257	-29.80**
	(0.766)	(12.19)
MSA Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Seasonal Fixed Effect	Yes	Yes
Observations	2,352	2,352
R-squared	0.402	0.297
Number of MSA	49	49

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

that there is no significant difference in common trends. Furthermore a negative and significant post treatment trend manifests after implementation.

5. Discussion

Our extensive analysis provides empirical evidence of a causal relationship between ride-sharing services and traffic congestion. An important question is what mechanism could possibly drive this main result. In the following, we offer a few explanations and our insights.

The first possible explanation is that Uber increases vehicle occupancy, thereby decreasing traffic congestion. Given that the number of commuters in an urban area does not grow at a high rate over a short period of time, ride sharing can reduce the total number of cars on the road by having more than one person in the car. A recent survey (Rayle et al. 2014) found that occupancy levels for ride-sharing vehicles averaged 1.8 passengers in contrast to 1.1 passengers for taxis in a matched pair analysis. According to the International Energy Agency (2005)[8], adding one additional person to every commute trip could achieve a saving of 7.7% on fuel consumption and a reduction of 12.5% on vehicle miles.

Second, the low cost travel mode of ride sharing reduces car ownership. In a growing number of cities, ride-sharing services like Uber provide low cost alternatives to car ownership.[9] Take San Francisco as an example, ride-sharing services are found to reduce car ownership, encourage more judicious and selective use of cars for particular trip purposes (Cervero and Tsai 2004). The availability of ride-sharing services also reduces consumers' incentives to purchase automobiles (Rogers 2015). Martin and Shaheen (2011) surveyed a sample of 6,281 households and found that each ride-sharing vehicle replaces 9 to 13 vehicles (postponed and sold) from the road. Another recent study of North American ride-sharing organizations shows that 15% to 32% of ride-sharing members sold their personal vehicles, and between 25% and 71% of members avoided an auto purchase because of ride-sharing.[10] A recent survey (Murphy 2016) of more than 4,500 shared mobility users in the seven study cities (Austin, Boston, Chicago, Los Angeles, San Francisco,

[8] http://www.worldenergyoutlook.org/media/weowebsite/2008-1994/weo2005.pdf

[9] http://www.usatoday.com/story/money/personalfinance/2014/11/08/ridesharing-lyft-uber/18482083/

[10] http://www.rmi.org/Content/Files/North\%20American\%20Carsharing\%20-\%2010\%20Year\%20Retrospective.pdf

Seattle and Washington, DC) also found that people who use more shared modes report lower household vehicle ownership and decreased spending on transportation.

Third, ride-sharing services can shift demand among different traffic modes. Researchers (Meijkamp 1998, Munheim 1998, Steininger et al. 1996) found evidence that those who used car sharing services drove significantly less than they did before they had used this service. Katzev (2003) conducted three studies on the early adopters of Car Sharing Portland and found that this service promoted trip "bundling" and greater use of alternative transportation such as bus riding, bicycling, and walking. Martin and Shaheen (2011) found that more car sharing users increased their overall public transit and non-motorized modal use.

Fourth, Uber's surge pricing strategy has the potential to delay or divert peak hour demands. The idea behind surge pricing is to adjust prices of rides so as to match driver supply to rider demand at any given time. Since the price of ride sharing in peak hours can surge quite high, riders who are price sensitive and flexible in their schedule may delay the travel time or choose to use public transit instead.

Finally, Uber increases vehicle capacity utilization. According to Cramer and Krueger (2016), in most cities, the efficiency of Uber is much higher than traditional taxis by having a higher faction of time and a higher share of miles having fare-paying passengers in their backseats. Higher capacity utilization means that Uber drivers will spend less time wandering streets searching passengers, which reduces excess fuel usage and traffic congestion.

6. Conclusion

As sharing economy grows, it is important to examine its potential impacts and implications. This paper studies one of the many social issues associated with ride-sharing services. Specifically, we empirically examine how the entry of Uber into major U.S. metropolitan areas influences traffic congestions. Taking advantage of a natural setting that Uber enters different cities at different times, we are able to compare the difference in congestion after and before Uber enters an urban area to the same difference for those urban areas without Uber service. We find that Uber can drastically reduce traffic congestion in urban areas. We performed comprehensive analysis to further assess the validity of the causal relationship. Our findings are consistent and robust to these extensions. We searched relevant literature in the transportation industry and summarized a few possible mechanisms that help explain our results.

This study adds to the ongoing debate over whether and how Uber impacts traffic congestion. Our rigorous empirical analysis provides additional evidence that on-demand ride sharing could actually be part of a solution to traffic congestion in major urban areas. This paper also has practical implications. The expansion of sharing economy faces tremendous challenges over the last few years. As discussed earlier, many cities have either banned or forced Uber to close down their business due to various concerns. Our results show that policymakers should also look at the positive side(s) of the sharing economy in order to make informed decisions.

This study has several limitations. First, we highlight a few mechanisms through which Uber decreases traffic congestion. Data limitations prevented us from directly testing those hypotheses in this paper. We call on future studies to further validate the conjectures. Additionally, because the sharing economy is a relatively new phenomenon, we are unable to examine the longer term consequences of Uber's entry on traffic congestion. Future work using longer panel data is worth to pursue.

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