Do On-demand Ride-sharing Services Affect Traffic Congestion? Evidence from Uber Entry

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Sharing economy platforms leverage information technology (IT) to provide services that re-distribute unused or underutilized assets to individuals who are willing to pay for the services. 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 the impact of Uber, a peer-to-peer mobile on-demand ride-sharing platform, on traffic congestion in the urban areas of the United States. Based on a unique data set combining data of Uber entry and the Urban Mobility Report, we empirically examine whether the entry of Uber on-demand ride-sharing services affects traffic congestion using a difference-in-differences framework. Our findings provide evidence that after entering an urban area, ride-sharing services such as Uber significantly decrease traffic congestion time, congestion costs, and excessive fuel consumption. To further assess the robustness of the main results, we perform additional analyses including the use of alternative measures, instrumental variables, placebo tests, heterogeneous effects, and a relative time model with more granular data. We discuss a few plausible mechanisms to explain our findings as well as their implications for the platform-based sharing economy.

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

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> "...sharing is to ownership what the iPod is to the eight-track, what the solar panel is to the coal mine. Sharing is clean, crisp, urbane, postmodern; owning is dull, selfish, timid, backward."
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> — *Share My Ride*, Mark Levine (New York Times, March 2009)

1. Introduction

In recent years, the platform-based sharing economy has received tremendous attention from major media and policy makers.[1] Sharing economy platforms aim at making efficient use of resources (e.g., labor and capital) by leveraging information technology-enabled digital infrastructure to lower the cost of matching the two sides of the platforms (e.g., buyers and sellers). First proposed by Benkler (2002), many studies subsequently explored the nature, design and effects of the sharing economy platforms (Avital et al. 2014, Botsman and Rogers 2011, Felländer et al. 2015, Sundararajan 2013, 2014). In 2011, TIME magazine named the sharing economy one of the ten ideas that will change the world. According to Price Waterhouse Coopers, the global revenues of the five key sharing sectors (ride/car sharing, P2P finance, online labor, P2P accommodation, and music/video streaming) have the potential to increase from around $15 billion to around $335 billion by 2025.[2]

On-demand ride-sharing platforms constitute a significant part of the sharing economy, with Uber being the pioneering company in the industry. The use of ride-sharing platforms is growing rapidly. According to Hall and Krueger (2016), Uber has attracted new "driver-partners" from fewer than 1,000 in January 2013 to almost 40,000 in December 2014. Currently, more than half of all American adults have heard of ride-sharing applications such as Uber and Lyft, out of which 15% have used these services (Smith 2016). The concept of ride sharing is actually not new. What is new about the on-demand ride-sharing platforms today is that they leverage the affordance of

[1] For example, Mark Warner, Senator from the Commonwealth of Virginia, has proposed a number of initiatives related to the sharing economy. https://www.warner.senate.gov/public/index.cfm/gig-economy

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

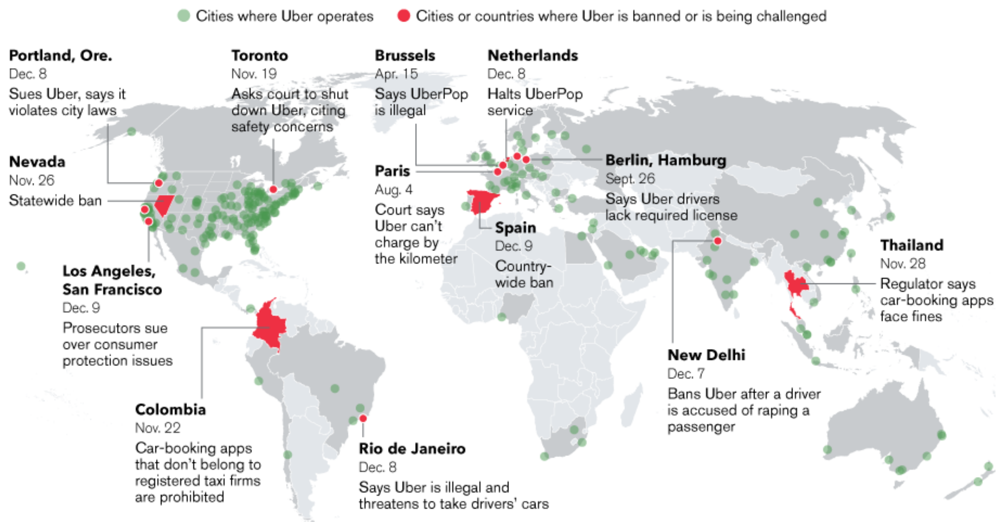
the latest digital technology to address the key limitations of traditional ride-sharing services. For example, platforms like Uber uses GPS signals on smartphones to match riders with drivers in real time. An efficient payment system is integrated with the application and payment is automatically settled at the end of a ride. These platforms also provide a rating system, which fosters trust and helps to create a positive experience for users. Additionally, many ride-sharing platforms have a dynamic pricing system to balance supply and demand, which helps to improve economic efficiency (Hall et al. 2015).

Despite the benefits of sharing economy business models, there have also been heated debates about their business practices. In fact, the disruptive force of the sharing platforms has raised challenges for many incumbent industries as well as debates among policy makers. Traditional industries such as the automotive and hotel industries were affected because consumers now have convenient and low-cost access to vehicles and lodging without the financial, emotional, or social burdens of ownership (Bardhi and Eckhardt 2015). Sharing economy also raised concerns about safety and workers' compensation (Malhotra and Van Alstyne 2014). Uber, for instance, hires drivers as contractors as opposed to employees. Therefore, drivers do not enjoy fringe benefits such as health insurance. As a result, the sharing economy models are often heavily regulated. Figure 1 shows a map of the worldwide cities where Uber operates and where it is being challenged.

In recent years, researchers have started to examine the (unintended) externality effects of the sharing economy platforms. Given ride sharing is an alternative mode of transportation, a few scholars began to examine its effects on the transportation industry. Rayle et al. (2014), for example, argue that on-demand ride-sharing fulfills an unserved demand of convenient, point-to-point urban travel. Wallsten (2015) finds evidence that the number of consumer complaints per taxi trip has declined as Uber expands into a city. A recent report by the American Public Transportation Association[3] highlights that ride-sharing services complement public transit, decrease car ownership and enhance urban mobility. Given traffic congestion is a key issue in the urban mobility literature,

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

Figure 1 **Where Uber Operates, and Where It's Been Challenged**



Note. Sources: Uber, Bloomberg reporting. Retrieved from: `https://www.bloomberg.com/graphics/infographics/uber-under-fire.html`

researchers have started to examine how on-demand ride sharing may have an effect on traffic congestion, using approaches such as simulation (Alexander and González 2015). However, the effect of on-demand ride sharing on traffic congestion is quite nuanced and simulation with strict assumptions may not fully capture the its empirical complexity. For example, there are at least two countervailing perspectives that entry of on-demand ride-sharing services into an urban area can have an impact on urban mobility, in particular, the traffic congestion. On one hand, by providing more convenient, less expensive services, on-demand ride sharing diverts non-driving trips like walking, transit, or cycling to a 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 vehicles.

Besides the simulation study conducted by Alexander and González (2015), a few other studies have delved into this important societal issue, yet the findings are inconclusive. One study from the New York Times estimates that Uber vehicles contribute to about 10 percent of traffic in Manhattan during evening rush hours, but acknowledged that it is difficult to measure the causal impact of Uber on the overall traffic increase.[4] In a separate study, the Office of the Mayor in New

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

York City released a report in January 2016, highlighting the city mayor's contention that Uber vehicles and other ride-sharing services had worsened traffic in Manhattan is unfounded.[5] In this paper, we leverage a natural experiment setting to empirically test the causal effect of Uber entry 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-differences (DID) approach 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 different urban areas in the United States from 1982 to 2014. Additionally, we conducted a comprehensive search and collected the entry time of Uber into an urban area from Uber's official website and major news outlets. In order to control the possible effects of other variables, we also collected data on fuel cost, socio-economic characteristics of urban areas, characteristics of road transport systems from the United States Census Bureau and the 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. Based on the DID analyses, we find empirical evidence that the entry of Uber indeed leads to a significant decrease in traffic congestion in the urban areas of the United States. Moreover, these results are consistent for different measures of traffic congestion. To assess the robustness of the results, we perform further analysis including the use of an alternative proxy measure for Uber usage, instrumental variables, heterogenous effects analysis and a relative time model with more granular data. We discuss a few plausible underlining mechanisms to explain our findings, and provide forward-looking insights about the broader impacts of ride-sharing services in the transportation industry, city infrastructure planning, and urban design.

The rest of the paper is organized as follows. Section 2 reviews relevant literature on digital infrastructure design, platform economics and ride sharing. Section 3 describes in detail the data

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

and our econometric specifications. Section 4 presents our findings as well as additional robustness checks. In Section 5, we discuss our results, implications, and provide a few underlining mechanisms to explain the results. Section 6 concludes and provides directions for future research.

2. Literature Review

2.1. Digital Infrastructure Design

Digital infrastructure brings 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, Alavi and Leidner 2001, Meyera and DeToreb 2001, Hirschheim et al. 2010). It's shared, unbounded, heterogeneous, open, and evolving socio-technical systems comprising an installed base of diverse information technology capabilities and their user, operations, and design communities (Hanseth and Lyytinen 2010). Many essential services in today's society, such as health care, finance and transportation, depend on digital infrastructure to function. How to effectively design, develop and manage digital infrastructure and platforms is, therefore, an important research topic. In a research commentary, Tiwana et al. (2010) presented a framework to understand platform-based ecosystems and discussed potential research opportunities in this area.

A few researchers argue that it is difficult to develop a digital infrastructure that satisfies the interests of all parties because users are highly heterogeneous in their interests and resources (Bowker and Star 2000, Hanseth 2000, Monteiro and Hanseth 1996, Star and Ruhleder 1996). To address this challenge, Gawer (2014) proposed a design theory that tackles dynamic complexity in the design process. Constantinides and Barrett (2014) described information infrastructure development as a collective action and proposed a bottom-up approach to govern infrastructure development. As digital platform scales, it is also important for platform owners to continuously innovate. Tiwana (2015) examined the effect of intra-platform competition on platform performance. Eisenmann et al. (2011), on the other hand, highlighted the concept of digital platform envelopment and discussed economic and strategic motivations of various envelopment attacks.

Lusch and Nambisan (2015) provided a new perspective of digital service innovation and discussed how information technology made the innovations technically feasible and economically viable.

2.2. Platform Economics and Impacts

Digital infrastructures have profound economic and social implications. In a seminal study, Parker and Van Alstyne (2005) described a model of two-sided network externality effects that were common in digital platforms and markets. Horton and Zeckhauser (2016) later developed a model of sharing economy rental markets and assess how these markets could change ownership and consumption decisions. Fradkin et al. (2015) study sources of inefficiency in matching buyers and suppliers in online market places. The authors conducted field experiments on Airbnb to study the determinants of reviewing behavior, the extent to which reviews are biased, and whether changes in the design of reputation systems can reduce that bias. Seamans and Zhu (2013) examined platform's pricing strategies by exploiting the gradual expansion of Craigslist into local newspaper markets. They showed that incumbent newspapers dropped their classified ad rates significantly after the entry of Craigslist. Zervas et al. (2015) estimated the relationship between Airbnb supply and hotel room revenue and found that an increase in Airbnb supply had a modest negative impact on hotel revenue.

Research examining social implications of digital platforms have gained momentum in recent years. Some representative works include Chan and Ghose (2014), who investigated whether the entry of Craigslist increased the prevalence of HIV. In a separate study, Greenwood and Agarwal (2015) also found a significant increase in the HIV incidences after the introduction of the online matching platform Craigslist. Bapna et al. (2016) estimated the causal effect of the anonymity feature on matching outcomes on online dating web sites. They found that anonymous users, who lost the ability to leave a weak signal, ended up having fewer matches compared with their non-anonymous counterparts.

Another stream of research examined the impacts of digital platforms on traditional industries such as the hotel and the transportation industries. Zervas et al. (2016), for example, estimated that each 10% increase in Airbnb supply resulted in a 0.37% decrease in monthly hotel room revenue. Wallsten (2015) explored the competitive effects of ride sharing on the taxi industry and found that Uber's popularity was associated with a decrease the consumer complaints per trip about taxi in New York City and decreases specific types of complaints about taxi in Chicago. These studies indicate the entry of peer-to-peer sharing platforms tend to benefit consumers by increasing competition for the incumbent industry.

2.3. Ride Sharing and Innovative Transportation

Ride sharing has a long history. In the late 1990s, cities such as Los Angeles (Golob and Giuliano 1996) and Seattle (Dailey et al. 1999) have implemented ride-matching services. The impacts of these traditional ride-sharing services on transportation have also been extensively studied. Baldassare et al. (1998) measured the likelihood of employees stopping solo-driving in response to various disincentives from ride sharing. Salomon and Mokhtarian (1997) discussed the effectiveness of various ride-sharing policies to reduce traffic congestion. Fellows and Pitfield (2000) provided a cost-benefit analysis and found that car sharing benefits individuals by cutting journey costs in half and benefited 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 a 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 CO_2 emissions were saved by ride sharing.

As discussed earlier, the new and innovative on-demand ride-sharing services were based on unique technology-enabled capabilities. Scholars have attempted to study the role and implications of these disruptive on-demand ride-sharing platforms. For example, Clark et al. (2014) found that peer-to-peer car sharing led to a net increase in the number of miles driven by car renters. van der Linden (2016) demonstrated that peer-to-peer car sharing was more prevalent in cities where a larger share of trips is taken by public transport and where there is a city center less suitable for vehicle access. Ballús-Armet et al. (2014), through a survey, estimated that about 25% of car owners would be willing to share their personal vehicles through peer-to-peer ride or car sharing. Using mobile phone data, Alexander and González (2015) demonstrated that, under moderate to high adoption rate scenarios, on-demand ride sharing would likely have noticeable effects in reducing congested travel times.

3. Data and Methods

Our research setting is the Uber platform, the largest 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 into an international corporation with billions of dollars of valuation. By April 12, 2016, Uber was available in over 60 countries and 404 cities worldwide. 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 application, she chooses a ride type (e.g., UberX, UberBlack, UberSUV) and set her location. The Uber platform automatically assigns a driver to the rider who request the service and then the driver on the other side of the platform responds to the request. The rider will see the driver's first name, profile picture and vehicle details, and can estimate time of arrival on the map. If the demand for rides is higher than the supply of cars, the rider will face surge pricing and can decide whether to hail a ride at that time. After a ride is completed, the payment is automatically collected and the rider can rate the driver and provide anonymous feedback about her trip experience.

3.1. Data

Our data come from a few archival sources. We retrieved the congestion data from the Urban Mobility Report (UMR), provided by the Texas A&M Transportation Institute. The Urban Mobility Report contains the urban mobility and congestion statistics for each of the 101 urban areas in the United States 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 entered an urban area.[6] Fourteen (out of 101) urban areas are not included in our sample because we were not able to verify the entry time. In order to control the possible effects of other variables, we also collected data on fuel cost, socio-economic characteristics of urban areas, characteristics of road transport systems from the United States Census Bureau and the Bureau of Economic Analysis. After merging different sources of data, we assembled a panel data comprises 957 observations spanning 11 years over 87 urban areas in the United States for our analyses. The list of Uber entry time into different urban areas is provided in the Appendix.

3.2. Dependent Variables

Our target outcome is the traffic congestion. We adopted a few 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. 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*, which are perhaps most important and direct measures of traffic congestion and the financial cost thereof. Specifically, delay time measures 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

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

dioxide 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.

Table 1 provides the summary statistics of the variables we discussed above to measure various aspects of traffic congestion. Since the variables delay time, delay cost and excessive fuel exhibit high skewness, we log-transformed these variables in our analyses.

Table 1 Definition and Summary Statistics of Five 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
DC	Annual congestion cost (million dollars)	1,553	2,492	70	16,346
EF	Annual excess fuel consumed due to congestion (Total gallons in thousand)	27,462	41,444	1,106	296,701

3.3. Control Variables

We control for the effects of a number of important variables that have been identified in the previous literature to influence traffic congestion, including the lane miles of road and the amount of travelers. 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.

3.4. Empirical Model and Specification

As discussed earlier, Uber enters different urban areas at different points of time. This allows us to use an entry model for econometric identification (Greenwood and Wattal 2017, Chan and Ghose 2014). Specifically, by repeatedly observing the congestion level in each urban area over time, we

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

could employ a difference-in-differences framework to examine the difference in congestion before and after Uber entry across multiple areas. Difference-in-Differences estimation has become an increasingly popular way to estimate causal relationships (Bertrand et al. 2004). It is appropriate when one wants to compare the differences in outcomes after and before the intervention for the treated groups to the same difference for the un-treated groups.[7] 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 effects and the time fixed effects, respectively; and ε_{it} denotes the error term. Fixed effects capture not only time-invariant factors but also allow the error term to be arbitrarily

[7] Note that Uber's decision to enter an urban area could be endogenous, which we further assess using an instrumental variables approach in Section 4.3.

correlated with other explanatory variables, thus making the model estimation robust (Angrist and Pischke 2008). We use robust standard errors clustered at the urban areas level to deal with potential issues of heteroscedasticity.

4. Results

In this section, we first report the main results with the DID specifications. We then report the findings of a few additional analyses, including an alternative measure for Uber entry, instrumental variables analyses, effect of competitor service Lyft, placebo tests, and more granular monthly level analyses.

4.1. Baseline Results

Table 3 reports the coefficient estimates of Equation (1) with each column using a different measure of traffic congestion. Overall, the estimates of the effect are statistically significant and negative for all measures of congestion. 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. Therefore, this set of baseline results provide empirical evidence that Uber entry significantly decreases traffic congestion in the urban areas of the United States. It is worth noting that for the control variables, 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 may be associated with its overall economic activities.

The results are not just statistically significant, but economically meaningful as well. Specifically, we estimate that after Uber enters an urban area, the total annual delay cost, delay time, and excess fuel on average decrease about 1.2%. For example, in the Phoenix urban area, that number translates into about $43.548 million reduction in annual delay cost, about 1.85 million hours reduction in total annual delay time, and 0.9 million gallons reduction in total annual excess fuel. From another perspective, after Uber enters an urban area, the Travel Time Index and Consumer Stress Index on average decrease about 0.19% and 0.3% respectively. On the national level, that translates into about $1.92 billion reduction in total annual delay cost, about 82.8 million hours reduction in total annual delay time, and 37.2 million gallons reduction in total annual excess fuel.

Table 3 Estimation Results of Uber Entry on Traffic Congestion

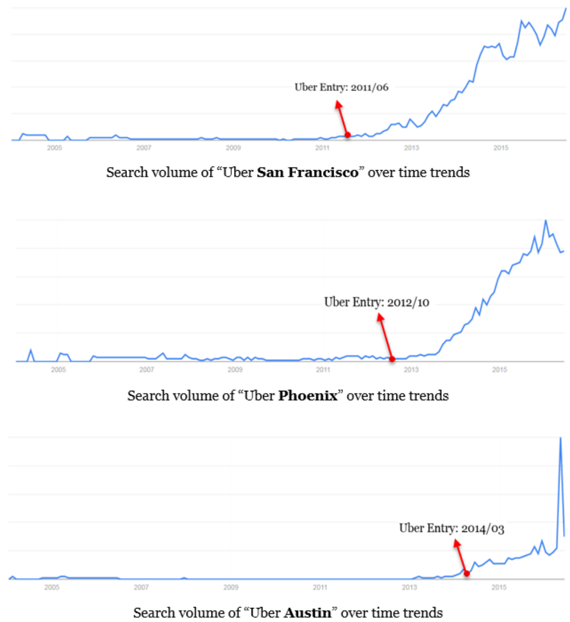
Dependent variables	(1) **TTI**	(2) **CSI**	(3) **log(Delay Time)**	(4) **log(Delay Cost)**	(5) **log(Excess Fuel)**
Uber Entry	-0.00237^{+}	-0.00377***	-0.0121**	-0.0121**	-0.0121**
	(0.00151)	(0.00139)	(0.00600)	(0.00599)	(0.00599)
log(GDP)	0.000364	0.000457	0.00391	0.00388	0.00389
	(0.000776)	(0.000697)	(0.00297)	(0.00297)	(0.00297)
log(Income)	0.0515***	0.0580***	0.255***	0.256***	0.256***
	(0.0133)	(0.0139)	(0.0696)	(0.0692)	(0.0692)
log(Population)	-0.0230	-0.0274	0.117	0.118	0.118
	(0.0390)	(0.0391)	(0.141)	(0.141)	(0.141)
log(Commuters)	-0.0316	-0.0325	0.603***	0.599***	0.599***
	(0.0400)	(0.0408)	(0.153)	(0.153)	(0.153)
Gasoline Cost	-0.00335	-0.00919	-0.0505	-0.0499	-0.0498
	(0.0132)	(0.0132)	(0.0573)	(0.0573)	(0.0573)
Diesel Cost	0.0169	0.0138	0.112	0.113	0.113
	(0.0154)	(0.0157)	(0.0889)	(0.0891)	(0.0891)
log(FDVMT)	0.00828	0.00780	0.0748	0.0759	0.0760
	(0.0138)	(0.0148)	(0.0659)	(0.0660)	(0.0660)
log(ASDVMT)	0.0185**	0.0130	0.0733*	0.0742*	0.0742*
	(0.00877)	(0.00841)	(0.0436)	(0.0436)	(0.0436)
Constant	0.745***	0.815***	-1.985	1.534	0.784
	(0.276)	(0.286)	(1.312)	(1.307)	(1.307)
Observations	957	957	957	957	957
Number of urban areas	87	87	87	87	87
R-squared	0.241	0.262	0.478	0.687	0.687

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

Thus far, we have used the Uber entry time to proxy for the implementation of Uber service. While extensively used in the entry model literature (Greenwood and Wattal 2017), Uber entry may not fully capture the actual usage of Uber services. In order to complement the Uber entry analysis, 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 of Google based on Google Search. It provides an index of the popularity of search terms. Therefore, we can proxy the popularity of Uber in a certain urban area based on the number of searches for the service in that region. Google Trends have been previously demonstrated to track economic activities (e.g., retail sales, automotive sales, home sales, and travel) in real time (Choi and Varian 2012). Wu and Brynjolfsson (2015) find that Google Trends are even more accurate in predicting housing sales and prices than traditional government-released indicators.

Figure 2 Time Trends of "Uber" + Sample Urban Areas on Google Trends



Note. Source: Google Trends

Table 4 Estimation Results Using the Alternative Measure of Uber Usage

	(1)	(2)	(3)	(4)	(5)
Dependent variables	**TTI**	**CSI**	**log(Delay Time)**	**log(Delay Cost)**	**log(Excess Fuel)**
log(Uber Usage)	-0.000421^{+}	-0.000626**	-0.00231**	-0.00231**	-0.00231**
	(0.000258)	(0.000243)	(0.00106)	(0.00106)	(0.00106)
log(GDP)	0.000373	0.000472	0.00395	0.00393	0.00393
	(0.000771)	(0.000691)	(0.00296)	(0.00295)	(0.00295)
log(Income)	0.0516***	0.0581***	0.256***	0.256***	0.256***
	(0.0133)	(0.0139)	(0.0695)	(0.0691)	(0.0691)
log(Population)	-0.0221	-0.0267	0.125	0.126	0.126
	(0.0391)	(0.0394)	(0.141)	(0.141)	(0.141)
log(Commuters)	-0.0323	-0.0331	0.597***	0.593***	0.593***
	(0.0401)	(0.0411)	(0.153)	(0.153)	(0.153)
Gasoline Cost	-0.00342	-0.00934	-0.0507	-0.0501	-0.0500
	(0.0132)	(0.0132)	(0.0573)	(0.0573)	(0.0573)
Diesel Cost	0.0167	0.0136	0.111	0.112	0.112
	(0.0153)	(0.0157)	(0.0886)	(0.0888)	(0.0888)
log(FDVMT)	0.00798	0.00742	0.0729	0.0740	0.0741
	(0.0138)	(0.0148)	(0.0658)	(0.0660)	(0.0660)
log(ASDVMT)	0.0186**	0.0131	0.0742*	0.0751*	0.0751*
	(0.00883)	(0.00845)	(0.0438)	(0.0438)	(0.0438)
Constant	0.744***	0.814***	-1.991	1.528	0.778
	(0.276)	(0.286)	(1.309)	(1.304)	(1.305)
Observations	957	957	957	957	957
Number of id	87	87	87	87	87
R-squared	0.242	0.262	0.479	0.687	0.687

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

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 in each time period. It's reasonable to assume that when an individual searches "Uber Phoenix" on Google, she is likely interested in the Uber service in the Phoenix area. Figure 2 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 after Uber entered San Francisco in June 2011, its search volume gradually increased. Similar patterns can be observed for Phoenix and Austin. Empirically, as expected, 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 usage of the Uber services. We address this problem by multiplying this variable with the Uber entry dummy variable as a new variable: *Uber Usage*.

Table 4 reports the results of our analysis using *Uber Usage* as our main independent variable. Once again, we find that our estimates are robust to this alternative measure.

4.3. Instrumental Variables

While entry model has been widely accepted and used (Greenwood and Wattal 2017, Chan and Ghose 2014), one may argue that Uber's decision to enter an urban area is not random. And there may be some factors that are correlated with both the entry decision and traffic congestion. In order to further assess the potential issue of endogeneity of Uber entry, we identified two instrumental variables (IV) to further assess the causal relationship between Uber and the traffic congestion. Based on an informal discussion with a Uber executive, we note that the decision for Uber to enter a location is partly dependent on the potential interest from that location. Therefore, we seek to identify instrumental variables that indicate potential interest for Uber, yet have little or no direct relationship with traffic congestion. The first instrumental variable we identified is the percent of population ages 65 and above. The percent of senior citizen population is not expected to be correlated with traffic congestion, but may influence the decision by Uber executives to not enter certain urban areas. Previous research (e.g., Warschauer 2004) have shown that senior citizens are more likely to experience digital inequalities. Since Uber represents a new phenomenon and is more likely to be adopted by tech-savvy younger generations, it is more (less) likely for Uber to offer services in urban areas with a higher (lower) percentage of young population. Recent statistics of Uber users (both drivers and passengers) provide anecdotal evidence on our reasoning. Based on Harris and Krueger (2015), the median 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.[8] Another IV we choose is the Google Trends search volume of ride-sharing services in the previous period. Search volume of previous period is a reasonable measure for consumer interest, which in turn can lead to actual future expenditures (Eppright et al. 1998). Therefore, we expect that the previous Google trends search volume could influence whether or not Uber is going to launch service in that location, Theoretically it has no impact on traffic congestion in the current period.

Following Angrist and Pischke (2008), we estimate the IV model with the two IVs identified above using a 2SLS approach.[9] Specially, we estimate the probability that Uber enters an urban area using the standard panel data linear probability approach and then included it in the second stage estimation. The diagnostic statistics show that the instrumental variables we identified are valid in terms of instrument strength and exogeneity. First, as per Table 6, we observe that there is a significant correlation between the IVs and the Uber entry. In addition, the first stage F statistic is significant and the CraggDonald Wald F statistics and the Kleibergen-Paap Wald rk F statistic pass the critical values suggested by Stock and Yogo (2005), alleviating the weak instrument concern. Finally, the Hansen J Statistics are statistically insignificant. Hence we can not reject the null hypothesis that the over-identifying restrictions are valid and the instrumental variables are exogenous.

[8] https://www.globalwebindex.net/blog/the-demographics-of-ubers-us-users

[9] We used Stata14's xtivreg2 procedure for parameter estimations of the IV models.

Table 5 Panel 2SLS Estimation Results

Dependent variables	(1) **TTI**	(2) **CSI**	(3) **log(Delay Time)**	(4) **log(Delay Cost)**	(5) **log(Excess Fuel)**
Uber Dummy	-0.010^{+}	-0.004	-0.094*	-0.096*	-0.094*
	(0.008)	(0.007)	(0.052)	(0.053)	(0.052)
log(Population)	-0.001	-0.022	0.333*	0.337*	0.334*
	(0.039)	(0.038)	(0.187)	(0.188)	(0.187)
log(GDP)	-0.000	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
log(Income)	0.060***	0.066***	0.273***	0.274***	0.273***
	(0.010)	(0.010)	(0.051)	(0.051)	(0.051)
log(Commuters)	-0.066**	-0.054*	0.314*	0.314*	0.314*
	(0.032)	(0.031)	(0.163)	(0.164)	(0.163)
Gasoline Cost	0.012	0.009	0.054	0.055	0.055
	(0.014)	(0.014)	(0.068)	(0.069)	(0.068)
Diesel Cost	0.015	0.014	0.105^{+}	0.105^{+}	0.105^{+}
	(0.016)	(0.016)	(0.069)	(0.069)	(0.069)
log(FDVMT)	-0.000	0.004	0.007	0.006	0.007
	(0.010)	(0.010)	(0.045)	(0.046)	(0.045)
log(ASDVMT)	0.022***	0.012*	0.098**	0.098**	0.098**
	(0.007)	(0.007)	(0.040)	(0.041)	(0.040)
Cragg-Donald Wald F statistic	10.446	10.446	10.446	10.446	10.446
Hansen J Statistics	0.021	0.030	0.118	0.145	0.118
P-value of Hansen J Statistics	0.8840	0.8621	0.7313	0.7034	0.7311
Observations	712	712	712	712	712
R-squared	0.2360	0.2889	0.5291	0.2904	0.5289
Number of urban areas	86	86	86	86	86

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.2$. 3. Stock-Yogo critical values (Stock and Yogo 2005) at 20% is 8.87 and Stock-Yogo critical values at 15% is 11.59.

Table 6 Panel 2SLS Estimation Results - First Stage

Dependent Variables	Uber Dummy
log(Previous Period's Google Trend)	0.0234* (0.0128)
Percent of Senior Citizens	-0.00022*** (0.0000598)
log(Population)	1.910 ** (0.870)
log(GDP)	-0.0245* (0.0241)
log(Income)	0.060 (0.283)
log(Commuters)	-2.075** (0.956)
Gasoline Cost	0.028 (0.472)
Diesel Cost	0.065 (0.367)
log(FDVMT)	-0.243 (0.237)
log(ASDVMT)	0.238 (0.212)
Observations	712
Number of urban areas	86
R-squared	0.668

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 reports the findings of this analysis, providing further empirical evidence of our main results. It should be noted that, for the dependent variable *CSI*, Uber entry no longer has a statistically significant effect. Given the IV analysis is an important robustness check, we must exercise caution when drawing the conclusion of the Uber effect on consumer stress levels. The first stage results and the fit statistics of the IV analysis are in Table 6.

4.4. Effect of the Competitor Lyft

Here, we consider and control for the effect from Uber's largest competitor in the US: Lyft. Following the same approach as above, we collected and verified data of Lyft entry time to different urban areas from major news outlets. The list of Lyft entry time into different urban areas is provided in the Appendix. We created the Lyft dummy variable and included this variable to Equation 1 to run the analyses.

Table 7 Results after Controlling for Lyft Entry Dummy

	(1)	(2)	(3)	(4)	(5)
Dependent variables	**TTI**	**CSI**	**log(Delay Time)**	**log(Delay Cost)**	**log(Excess Fuel)**
Uber Dummy	-0.002^{+}	-0.003**	-0.010*	-0.010*	-0.010*
	(0.002)	(0.001)	(0.005)	(0.005)	(0.005)
Lyft Dummy	-0.002	-0.003	-0.006	-0.006	-0.006
	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)
log(GDP)	0.000	0.001	0.004	0.004	0.004
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
log(Income)	0.052***	0.058***	0.257***	0.256***	0.257***
	(0.013)	(0.014)	(0.069)	(0.070)	(0.069)
log(Population)	-0.0221	-0.026	0.121	0.120	0.121
	(0.039)	(0.039)	(0.141)	(0.141)	(0.141)
log(Commuters)	-0.033	-0.034	0.597***	0.600***	0.597***
	(0.040)	(0.041)	(0.153)	(0.154)	(0.153)
Gasoline Cost	-0.002	-0.008	-0.047	-0.048	-0.047
	(0.013)	(0.013)	(0.057)	(0.057)	(0.057)
Diesel Cost	0.016	0.013	0.110	0.109	0.110
	(0.015)	(0.015)	(0.087)	(0.087)	(0.087)
log(FDVMT)	0.008	0.007	0.074	0.073	0.074
	(0.014)	(0.015)	(0.066)	(0.066)	(0.066)
log(ASDVMT)	0.019**	0.014	0.076*	0.075*	0.076*
	(0.009)	(0.009)	(0.044)	(0.044)	(0.044)
Observations	957	957	957	957	957
Number of urban areas	87	87	87	87	87
R-squared	0.243	0.264	0.687	0.478	0.687

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.20$

Table 7 presents the results with Lyft entry dummy included in our model. We find that the coefficients for Lyft dummy are consistently negative but not significant. More importantly, adding the Lyft dummy does not affect the sign and significance of Uber dummy. Since Uber is the biggest and most popular ride-sharing platform in the US and the scale of operation and market share of Uber is much larger than Lyft, it is reasonable to observe the effect of ride-sharing services on traffic congestion comes primarily from Uber.

4.5. Placebo Tests

According to Angrist and Pischke (2008), a key assumption of the DID model is the parallel trend assumption. It is important to further demonstrate that the causal effect does not manifest prior to the actual Uber entry. Here, we conduct a systematic placebo test of our results using a permutation approach suggested by Abadie et al. (2010). Specifically, we loop through 5000 permutations by randomly shuffling the Uber entry time in the pre-treatment period using a pseudo random number generator (Matsumoto and Nishimura 1998). We re-estimate the DID model using the shuffled treatment time and save the coefficient estimates for each permutation. If the parallel trend assumption is valid, the distribution of the coefficient estimates in the placebo test should be centered around zero because the placebo Uber entry were not real and should not create any systematic differences regarding traffic congestion.

Table 8 Results of the Placebo Tests

	Placebo Coef. Mean	Placebo Coef. Std. Dev.	Uber Dummy Coef.
TTI	-0.00016	0.00079	-0.00237^{+}
CSI	-0.00039	0.002	-0.00377***
log(Delay Time)	-0.000809	0.0039	-0.0121**
log(Delay Cost)	-0.000814	0.0039	-0.0121**
log(Excess Fuel)	-0.0008	0.0039	-0.0121**

1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^{+}p < 0.15$

Table 8 summarizes the mean and standard deviations of the coefficient estimates for the 5000 runs, along with the actual estimate of the Uber effect we observed from data with actual Uber entry. We observe that the average coefficient estimate of the placebo test is close to zero. Further, the real coefficient of Uber dummy is outside the 95% confidence interval of the placebo coefficient for TTI, Delay Time, Delay Cost, and Excess Fuel, and outside the 90% confidence interval for CSI. These results suggest that the DID assumption is not violated for the main analyses, which further lend credibility to our findings.

4.6. 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. Note that although the monthly data is more granular, offering more observations and a higher statistical power, it is not as comprehensive. For example, data on Delay cost, Delay time and excess fuel consumption are not available in the monthly level data. As a result, we report results using only TTI and congested hours (CH) as dependent variables in our monthly level data analysis. Also, it is quite limited in number of urban areas covered. Therefore, it is presented as another robustness check.

The summary statistics of the two dependent variables are reported in Table 9.

Table 9 Definition and Summary Statistics of DVs 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

4.6.1. DID Analysis We adopt the same DID model (Equation 1) and apply it on this monthly data set. Since traffic patterns typically exhibit strong seasonal fluctuations, we include the seasonal fixed effect in our model by adding 11 month dummies. The results of the monthly level analysis are shown in Table 10.

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 a significant and negative effect on congestion. The diversity of Uber service refers to the number of car types that is available to a customer when she opens the application in a geographical area; different car type services come with different fares. We believe that the diversity and multiplicity of Uber services will stimulate more Uber usage, thus reducing congestion. Table 10 shows that as the diversity of Uber service increases, both TTI and CH decrease.

Table 10 **Estimation Results of Impact of Uber Entry on Congestion Using Monthly Level Data**

	(1) TTI	(2) log(Congested Hours)
Uber Entry	-0.0111*	-0.275**
	(0.00587)	(0.121)
Diversity of Uber Service	-0.0624***	-1.096***
	(0.00453)	(0.0886)
log(GDP)	-0.0592	-112.5
	(4.381)	(58.05)
log(Income)	9.57e-06*	8.68e-05
	(5.01e-06)	(7.24e-05)
log(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
Number of MSAs	49	49
R-squared	0.392	0.294

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.6.2. Heterogeneous Effects It is natural to believe that the Uber effect on traffic congestion varies for different metropolitan areas. For example, in metropolitan areas where individuals are more reliant on personal cars or areas that have less public transportation, one would expect a stronger effect. In order to test for such heterogeneity, we collected data on hourly parking rate for 22 MSAs and matched the data onto our monthly data set. We re-estimate our model by adding an interaction term of Uber dummy and *log(MedianHourlyParkingRate)*. Table 11 reports the estimates. As expected, we find that the effect of Uber entry (in reducing traffic congestion) is smaller for MSAs with a higher parking rate because of the positive and significant estimates of the interaction term.

4.6.3. Relative Time Analysis The richness of the monthly level data allows us to conduct a relative time analysis (Angrist and Pischke 2008). The advantage of the relative time model over DID is that it further helps evaluate the parallel trends assumption.

Our relative time model is specified in Equation (2). Following Autor (2003), Bapna et al. (2016), Chan and Ghose (2014), Greenwood and Wattal (2017), we include a series of time dummies

Table 11 Results for Uber Dummy Interaction with Parking Rate

	(1) **TTI**	(2) **log(Congested Hours)**
Uber Dummy	-0.067***	-0.168**
	(0.016)	(0.060)
Uber Dummy * log(MedianHourlyParkingRate)	0.036***	0.104**
	(0.010)	(0.037)
log(GDP)	-0.001	-1.591**
	(0.311)	(0.678)
log(Income)	0.305	0.858
	(0.205)	(0.530)
log(Population)	1.700***	5.262***
	(0.423)	(1.416)
MSA Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Seasonal Fixed Effect	Yes	Yes
Observations	1,056	1,056
Number of MSAs	22	22
R-squared	0.550	0.411

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

$(j = t-6, ..., t+6)$ that represent the chronological distance between an observation period, t, and the timing of treatment in MSA i. The key feature of this relative time model is that it estimates the effect of Uber entry while controlling for the absolute time effect.

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

In this model, $Congestion_{it}$ represents the two dependent variables: TTI and CH. The variable μ_i indicates whether or not Uber will ever enter area i, and ϕ is the relative time dummies. Similar as Table 10, we include two kinds of time fixed effects in our model: a year fixed effect and a seasonal fixed effect.

Table 12 presents the results of the relative time analysis. There are several interesting observations. First, the results are quite 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 that there is no significant difference in common trends. Furthermore, a negative and significant post-treatment trend manifests only after Uber entry.

Table 12 Estimation Results of the Relative Time Model

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

1. Cluster-robust standard errors in parentheses. 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5. Discussion

As sharing economy scales, it is important to examine its potential impact and implications thereof. This paper studies one of the many social issues associated with on-demand ride-sharing platforms. Specifically, we empirically examine how the entry of Uber into major U.S. urban (or metropolitan) areas influences traffic congestion. Leveraging a natural experiment setting wherein Uber enters different urban areas at different points in time, we are able to compare the differences in congestion before and after Uber enters an urban area to the same difference for those urban areas without Uber service. We find that on average, Uber entry significantly reduces traffic congestion in urban areas. We performed comprehensive analyses to further assess the validity of the causal relationship. Our findings are consistent and robust to these extensions. This study provides empirical evidence that adds to the ongoing debate over whether and how Uber impacts the society (Greenwood and Wattal 2017, Alexander and González 2015, Burtch et al. 2016), with a specific focus on traffic congestion (Goodwin 1996, Merrill and Coote 2015). While prior research has used an entry model to examine the effect of ride sharing on social problems such as vehicle-related homicides (Greenwood and Wattal 2017), this is a first comprehensive and causal study on how ride sharing affects traffic congestion. This study also contributes to the broader literature on the societal impact of digital infrastructure and platforms (Tilson et al. 2010, Henfridsson and Bygstad 2013, Parker and Van Alstyne 2014, Eisenmann et al. 2011, Chan and Ghose 2014, Seamans and Zhu 2013).

There are a few possible mechanisms that can drive our results. First, ride sharing helps to increase vehicle occupancy by having more than one person in the car, thus potentially reducing the total number of cars on the road and decreasing traffic congestion. A recent survey by Rayle et al. (2014) actually provides evidence that occupancy levels for ride-sharing vehicles averaged 1.8 passengers in contrast to 1.1 passengers for taxis. The availability of ride-sharing services could also reduce consumers' incentives to purchase automobiles (Rogers 2015). Murphy (2016) surveyed more than 4,500 shared mobility users in seven cities (Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle and Washington, DC) and found that individuals who use more shared transportation modes report lower household vehicle ownership. Second, a unique feature of the ride-sharing platforms (such as Uber) is its dynamic surge pricing. 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 hailing a car in peak hours can surge quite high, riders who are price sensitive may choose to delay their travel schedule or use public transit instead. This helps to smooth out trip demand throughout the day and/or shift demand to other transport modes (such as bus riding, bicycling, and walking), thus reducing traffic congestion. Third, another interesting phenomenon of the disruptive mobility is that it helps to increase vehicle capacity utilization. Cramer and Krueger (2016) found that the efficiency of Uber car utilization is generally higher than traditional taxis in most cities, due to the advancements of GPS and smartphone technologies, integration of electronic payment systems in the platform, and sophisticated algorithms to match demand with supply. The higher capacity utilization means that Uber drivers will spend less time wandering streets searching passengers, which reduces excess fuel usage and traffic congestion.

Our study is likely to generate more discussions about whether and how digital platforms (such as Uber) can impact transportation, city infrastructure planning, and urban development. As sharing economy business models (e.g., Uber and Airbnb) expand, they face strong resistance from not only the traditional industries they are disrupting, but also social and political pressures to protect the public. In fact, many cities have proposed rules to limit and regulate how these digital platforms should operate due to various concerns. Our results suggest that these innovative platform-based services could be a solution to a broader set of social issues (e.g., traffic). Weyl and White (2014) make a compelling case that the way city governments regulate digital platforms (such as Uber) may be problematic. Hence these platform-based business models should be given room to grow. Policymakers will need to balance the positive effects against the unintended negative consequences of these platforms in order to make informed decisions. Over time, we can learn and develop guidelines as we observe how they work. For ride-sharing platform operators, such as Uber and Lyft, it's important for them to understand that ride-sharing platforms have provided unintended positive externalities to the society and they should research how to effectively design the platforms to enable the technological affordance that would enhance these positive externalities.

This study has several limitations. First, we highlighted a few mechanisms through which Uber decreases traffic congestion. Data limitations prevented us from directly testing those mechanisms in this paper. We call for future studies to identify the mechanisms that drive the main results. The second limitation is the generalizability of our findings. Our results are based on traffic patterns in the United States. So they cannot be directly generalized to other countries (e.g., the United Kingdom) without further rigorous empirical analysis. Other contextual factors such as public acceptance of ride sharing, culture and government policies should be considered in order to make a sound conclusion. Third, because the sharing economy is a relatively new phenomenon, we are unable to examine the long-term consequences of Uber's entry on traffic congestion. Future work using longer panel data is worth to pursue. Lastly, in our main analyses, we used a standard entry model approach (Chan and Ghose 2014, Greenwood and Wattal 2017) to estimate the causal effect of Uber entry, and we further used instrumental variables to further assess the validity of the findings. However, Uber's decision to enter a location is unknown and could still be endogenous. While we believe we have leveraged the best research design available, future research may further establishes a causal relationship using other identification strategies.

6. Conclusion

Digital infrastructure and platforms are rapidly evolving, thanks in part to advances in mobile technology, machine learning, and artificial intelligence (Yoo et al. 2010, Henfridsson and Bygstad 2013, Constantinides and Barrett 2014, Parker et al. 2016). We believe the landscape of on-demand ride sharing will change dramatically in the years to come. Two major trends are currently emerging in the auto industry: automation and the shared use of vehicles. It will not be long before we see the shared use of driverless cars. In fact, this is already happening. Uber and other companies are testing autonomous vehicles and are looking to mass-produce and use them to replace their current model of fleets of drivers.[10] When that happens, its effects will be far reaching and the concept of transportation will be fundamentally changed. Of course, the sticky point is how consumers are going to respond to such disruptive technologies. At this point, it is not clear if consumers will fully utilize a shared vehicle network, purchase privately owned autonomous vehicles, or share those cars with other users. Each of these scenarios could have different implications on urban design and complicates a city's efforts to plan ahead.[11] It is our hope that our study is one of the first few that will attract researchers and practitioners to engage in meaningful open discussions in this exciting domain of on-demand ride sharing.

[10] `https://techcrunch.com/2017/03/27/ubers-autonomous-cars-return-to-the-road-in-san-francisco-today/`

[11] `http://doggerel.arup.com/as-a-driverless-future-dawns-should-we-still-build-parking/`

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Appendix: Uber and Lyft Entry Times

Urban Area	City	Uber Entry	Lyft Entry
Akron OH	Akron	2014/08	2014
Albany-Schenectady NY	Albany-Schenectady	N/A	2014
Albuquerque NM	Albuquerque	2014/04	2014
Allentown PA-NJ	Allentown	2015/01	2016
Atlanta GA	Atlanta	2012/08	2013
Austin TX	Austin	2014/03	N/A
Bakersfield CA	Bakersfield	2014/06	2014
Baltimore MD	Baltimore	2013/02	2013
Baton Rouge LA	Baton Rouge	2014/07	2017
Beaumont TX	Beaumont	N/A	N/A
Birmingham AL	Birmingham	2015/02	2017
Boise ID	Boise	2014/10	2016
Boston MA-NH-RI	Boston	2012/09	2013
Boulder CO	Boulder	2014/08	2013
Bridgeport-Stamford CT-NY	Bridgeport-Stamford	2014/04	2016
Buffalo NY	Buffalo	N/A	2014
Charleston-North Charleston SC	Charleston, SC	2014/07	2016
Charlotte NC-SC	Charlotte	2013/09	2013
Chicago IL-IN	Chicago	2011/09	2013
Cincinnati OH-KY-IN	Cincinnati	2014/03	2014
Cleveland OH	Cleveland	2014/04	2014
Colorado Springs CO	Colorado Springs	2014/05	2014
Columbia SC	Columbia	2014/07	2017
Columbus OH	Columbus	2013/12	2016
Corpus Christi TX	Corpus Christi	2014/05	2014
Dallas-Fort Worth-Arlington TX	Dallas	2012/09	2013
Dayton OH	Dayton	2014/08	2016
Denver-Aurora CO	Denver	2012/09	2013
Detroit MI	Detroit	2013/03	2014
El Paso TX-NM	El Paso	2014/06	2017
Fresno CA	Fresno	2014/02	2014
Grand Rapids MI	Grand Rapids	2014/07	2016
Greensboro NC	Greensboro	2014/06	2016
Honolulu HI	Honolulu	2013/12	2014
Houston TX	Houston	2014/02	2017
Indianapolis IN	Indianapolis	2013/06	2013
Jackson MS	Jackson	2015/12	2016
Jacksonville FL	Jacksonville	2014/01	2014
Kansas City MO-KS	Kansas City	2014/05	2014
Knoxville TN	Knoxville	2014/08	2016
Laredo TX	Laredo	N/A	N/A
Las Vegas-Henderson NV	Las Vegas	2014/11	2015

Little Rock AR	Little Rock	2014/11	2015
Los Angeles-Long Beach-Anaheim CA	Los Angeles	2012/03	2013
Louisville-Jefferson County KY-IN	Louisville	2014/04	2014
Madison WI	Madison	2014/03	2014
Memphis TN-MS-AR	Memphis	2014/04	2014
Miami FL	Miami	2014/06	2014
Milwaukee WI	Milwaukee	2014/03	2014
Minneapolis-St. Paul MN-WI	Minneapolis-St. Paul	2012/10	2014
Nashville-Davidson TN	Nashville	2013/12	2013
New Haven CT	New Haven	2014/04	2014
New Orleans LA	New Orleans	2014/09	2016
New York-Newark NY-NJ-CT	New York City	2011/05	2014
Oklahoma City OK	Oklahoma City	2013/10	2014
Omaha NE-IA	Omaha	2014/05	2014
Orlando FL	Orlando	2014/06	2014
Pensacola FL-AL	Pensacola	2014/12	2017
Philadelphia PA-NJ-DE-MD	Philadelphia	2012/05	2015
Phoenix-Mesa AZ	Phoenix	2012/10	2013
Pittsburgh PA	Pittsburgh	2014/03	2014
Portland OR-WA	Portland	2014/12	2016
Providence RI-MA	Providence	2013/09	2014
Provo-Orem UT	Provo-Orem	2015/09	2014
Raleigh NC	Raleigh-Durham	2014	2014
Richmond VA	Richmond	2014/08	2016
Rochester NY	Rochester	N/A	2017
Sacramento CA	Sacramento	2013/01	2013
Salt Lake City-West Valley City UT	Salt Lake City	2014/05	2014
San Antonio TX	San Antonio	2014/03	2015
San Diego CA	San Diego	2012/06	2013
San Francisco-Oakland CA	San Francisco	2010/06	2012
Sarasota-Bradenton FL	Sarasota	2014/12	2016
Seattle WA	Seattle	2011/08	2013
Spokane WA	Spokane	2014/05	2014
Springfield MA-CT	Springfield	2015/04	2017
St. Louis MO-IL	St. Louis	2014/10	2014
Stockton CA	Stockton	2014/05	2014
Tampa-St. Petersburg FL	Tampa Bay	2014/04	2014
Toledo OH-MI	Toledo	2014/06	2014
Tucson AZ	Tucson	2014/06	2014
Tulsa OK	Tulsa	2014/03	2014
Virginia Beach VA	Virginia Beach	2014/05	2014
Washington DC-VA-MD	Washington DC	2011/11	2013
Wichita KS	Wichita	2014/08	N/A
Winston-Salem NC	Winston-Salem	2014/06	2016
Worcester MA-CT	Worcester	2014/10	2017