THE EFFECTS OF TRANSPORTATION NETWORK COMPANIES ON TRAFFIC CONGESTION

By

CHOI, Eun Hye Grace

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

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Abstract

This study examines the relationship between the entry of Transportation Network Companies (TNCs) and traffic congestion within urban areas of the United States. For this analysis, I use the Texas A&M Transportation Institute Urban Mobility Report (UMR) and data on TNCs (namely, Lyft and Uber) collected from the local news of target cities to identify the entry of TNCs in each of the 101 urban areas. Specifically, this paper analyzes the effect of the entry of TNCs on traffic congestion using the fixed effects approach and instrumental variable strategy to account for possible endogeneity problems. The findings indicate that the entry of TNCs has a negative impact on mitigating traffic congestion. These findings are inconsistent with previous studies.

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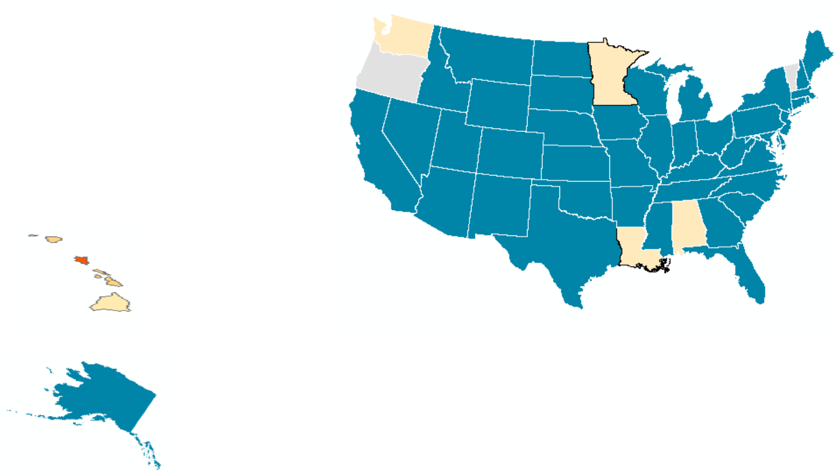
1. Introduction and Background

The rapid expansion of transportation network companies (TNCs), such as Lyft and Uber, that provide app-based ride-sourcing services has led policy makers and regulators in 48 American states, although more prominently in certain states, to quickly pass some sort of TNC-related legislation (Goodin and Moran, 2017). As policy makers across the United States continue to work toward establishing well-targeted interventions to keep innovation-the new travel options that allow connecting passengers seeking for rides with drivers willing to provide with their existing personal vehicles-working harmoniously, numerous traffic-related issues regarding TNCs have been raised in public debate.

Figure 1 U.S. State-Level TNC Legislation



Source: Texas A&M Transportation Institute

In the ongoing debate, there are two dominant perspectives on the impacts of TNCs: innovation and disruption. The innovation perspective views TNCs as having enormous potential to alleviate excess vehicle traffic congestion in American cities by replacing solo drivers with shared network services (Feigon and Murphy, 2016; Shiryaevskaya, 2017; Williams, 2016). Contrary to this positive view, the alternative perspective identifies TNCs as an ever-growing contributor to the problem of traffic congestion as TNCs attract people to use vehicle transportation who would otherwise likely walk or use public transit (Komanoff, 2017; Morrell, 2017; Wallsten, 2015; Fraiberger and Sundararajan, 2017). Table 1 illustrates how the existence of TNCs can impact traffic congestion in more detail. While many have discussed and studied the potential effects of TNCs, there is still limited analytical evidence. The purpose of this paper extends current research in the field in a number of noteworthy ways, including providing missing empirical analysis.

This paper focuses on the impact that TNCs have on traffic congestion, specifically focusing on the cases of Uber and Lyft, the two largest TNC platforms, ranked second and fifteenth respectively out of 215 companies in the CB Insight's database of unicorn companies (CB Insights, 2019). However, as I explain more formally in the following section, causal identification of the relationship between TNCs and traffic congestion faces two primary obstacles: data availability and endogeneity. To conduct the analysis, I retrieved the best available traffic congestion data in relevant urban areas and reviewed local news media to determine if or when TNCs arrived in each area.

To identify the causal impact of TNCs on traffic congestion, I made use of instrumental variables and employed a difference-in-difference identification strategy to address for the potential endogeneity. For both identification strategies, I included a set of explanatory variables that simultaneously affect traffic congestion and TNCs, allowing me to move toward the assumption needed to lessen potential endogeneity concerns. The empirical results for all key coefficients of interest were positive in all cases, indicating that the entry of TNCs increases traffic congestion.

Finally, in robustness checks, I used only large population datasets instead of a broader set of urban areas for comparisons. According to Cortright (2010), the UMR states that these areas account for about 81% of the nation’s total estimated congestion costs, such as loss of time and excess fuel consumption. TNC ridership growth has also accelerated in congested and densely populated metropolitan areas (Schaller Consulting, 2018). Though not conclusive, these results serve to reduce the bias of the estimated coefficients and account for spurious relationship. Moreover, obtaining similar results via different dependent variables lends credibility to the idea that the impact of TNCs on traffic congestion, rather than other factors, is what is being accounted.

1.1 Literature Review

Transportation Network Companies and Traffic Congestion

Previous studies suggest that TNCs have the potential to provide timely and efficient forms of transportation and to reduce vehicle traffic congestion by substituting individual private car ownership with ride-sharing services (Shaheen and Chan, 2015). For example, car-sharing systems reduced the net number of vehicles owned by urban residents within Calgary, Alberta, Vancouver, British Columbia, and Washington, DC. OECD/ITF(2015) findings suggest that P2P services translate into reduced greenhouse gas emissions due mainly to the impact of TNCs on the VMT. According to Thornley (2017), privately owned vehicles are used less than shared vehicles, which reduces the number of cold starts; this means shared vehicles lead to increased emissions when compared to privately owned vehicles. In line with previous studies, Murphy et al. (2016) identifies that TNC users are more likely to also use public transit. Furthermore, Davis and Dutzik (2012) suggests that these new mobility services are partially responsible for decreased rates of demand for private vehicle ownership by younger Americans; this suggests that the demand for ride-sharing services will continue to grow in significance.

Pew Research Center (2016) finds that 86% of TNC users indicate that TNCs save time and stress, suggesting that commuters in areas with heavy traffic may choose to use TNCs over other transportation options. As of yet, it is not clear whether the entry of TNCs into American cities will ultimately increase traffic congestion by attracting people who would otherwise use public transit or alleviate excess vehicle traffic congestion by replacing solo drivers with shared network services (Refer to Table 1).

The paper proceeds as follows. Section 2 reviews the related literature on TNCs. Section 3 describes the empirical models and data set for the analysis. Section 4 presents the results of the main analysis. Section 5 concludes.

Table 1 - The perspectives on the impact of TNCs

Positive	Negative
① Reduce solo drivers • Leads to efficient allocation of spare capacity and address parking needs: save travel cost • Mitigate traffic -> reduce travel time • Conserve fuel • Reduce air pollution • Reduce car ownership • Reduce vehicle miles travelled • Eliminates transport infrastructure costs (Gavin, 2016) ② Meet the public's demand for convenient and affordable transportation services (Schaller Consulting, 2017) when there is a shortage of cab availability (Bliss, 2017) ③ TNC users are more likely to use the public transport (Shared Use Mobility Center, 2016) ④ Data-driven driving (Simons, 2017; Lee, 2017) • Potential to mitigate congestion and reduce vehicle emission (Schaller Consulting, 2017) ⑤ Improve traffic and save money (Simons, 2017) Shared motilities are intensely used • Cars have shorter life cycles and less CO2 emissions (IFT, 2015) ⑥ Maximize impaired-driving reduction (TTI, 2017) ⑦ Uber is a complement for public transit(Hall, Palsson, Price, 2018)	① Attract more drivers on the road • Rise of private car transport • Increase of 600 million driving miles from 2013-2016 (Roberts, 2017) • A net increase of 600 million Vehicles Miles Traveled (Komanoff, 2017) ② Attract people who would otherwise walk, bike, or use public transports ③ Add congestion during traffic hours • Incentive to drive at peak hours surge pricing problems (Wang, 2015) ④ Potential indirect impacts from TNCs activities(Hughes, 2017) • Blocking traffic and bike lanes • Traffic violations such as illegal U-turns (Kunkle, 2016) ⑤ Negative impact on the taxi industry (TTI, 2017)

Source: Multiple Sources

2. Data and Methodology

The paper examines the effects of TNCs on traffic congestion using a metropolitan statistical area-level panel dataset that spans 8 years from 2007 to 2014, covering 97 metropolitan statistical areas within 42 states across the U.S. The analysis is based on a panel dataset that consists primarily of four sets of parameters: 1) traffic congestion, 2) TNCs entry, 3) a set of control variables, and 4) two instrumental variables. Data for each of the four parameters come from a variety of sources, therefore to obtain a consistent dataset, all data were collected at the metropolitan level and integrated using the urban area's special code, Geofips. The details of the variables are discussed in more detail below. I restrict the observation from period 2007 to 2014, given that the earliest entrance for Uber is 2011 and 2012 for Lyft. The completed dataset covers 567 observations broadly described in Tables 2 and 3.

The indicators of traffic congestion and TNCs

As noted above, the goal of this paper is to identify the causal effect of TNC entry on traffic congestion. However, there are several limitations to drawing firm conclusions regarding the impact of TNCs. The first limitation is data availability. Specifically, the actual volumes of TNCs and of traffic congestion, albeit for different reasons, are difficult to measure. Therefore, a key step in the empirical strategy is finding convincing proxy measures of traffic congestion and TNCs.

The general definition of traffic congestion, mainly characterized by average speed, flow, density, delay, and travel time variability, can be used to analyze congestion levels in urban areas (Amudapuram Rao and Kalaga Rao, 2012). The 2015 Urban Mobility Report, the main dataset I used for my overall analysis, has been widely referenced in several academic papers (VPTI, 2018; ATC, 2017; Sisiopiku, 2017; Rao, 2012; Sweet, 2011; Toledo, 2011; Chen, 2010; Hymel, 2008) and acknowledged as the "the best available means of comparing congestion levels in different regions and tracking changes in regional congestion levels over time." (Downs, 2004, pp.17).

For this analysis, $Trafficcongestion_i$ is based on several urban mobility and congestion-related statistics reported in the dataset provided by the Urban Mobility Report (UMR). These include Travel Time Index, Travel Delay, Congestion Cost, and Excess Fuel Consumed. The details of the 5 variables are as follows.

Traveldelay is the time wasted due to speeds that are slower than free-flow speeds. **Congestioncost** represents the value of congestion-related costs: the time delayed and the wasted fuel in total dollars. Texas Transport Institute collaborated with Wisconsin Energy Institute to develop the **ExcessFuelConsumed**, which calculates the fuel efficiency in congestion and free-flow based on the carbon dioxide emission estimates. The summary statistics of the five performance measures of traffic congestion are given in Table 2.

Table 2-Description and Summary Statistics for Measures of Traffic Congestion

Variables	Description	Mean	Std. Dev.	Min	Max
Log_TD	Log Annual hours of Total Delay (billion hrs)	3.64	.33	2.08	4.45
Log_CD	Log Annual congestion cost (billions of 2014 dollars)	6.59	1.12	3.91	9.70
Log_EF	Log Annual excess fuel consumed (billion gallons)	9.46	1.10	6.75	12.6

In this analysis, the key parameter of interest is the coefficient on TNCs' entry. However, the actual trip volumes of TNCs are difficult to measure because these services are still relatively new, and there is a lack of information available about the actual trip volumes of TNCs due to TNCs' privacy and competition concerns. (TTI Report).

Instead of via direct observation, the data for Uber and Lyft was obtained from cities' local news reports in order to uniquely identify when TNCs were officially launched in various American cities. The independent variable, TNCs, used in this paper equals 1 if Lyft or Uber has been introduced in the urban area, 2 if both Lyft and Uber have been introduced, and 0 if neither has been introduced.

Control variables

Table 2 summarizes the variety of control variables explored within this paper; public transit services, walking, and "no vehicles" data was obtained from ACS. VPTI (2018) and Beaudoin and Lawell (2017) advocate public transit and walking as means to relieve traffic congestion. Flow (2016) provides general findings on the congestion-related and the socio-economic impacts of walking. Increased car ownership has been widely accepted by researchers as one of main contributors to increased traffic congestion.

Demands for road space are strongly correlated with the socio-economic factors of economy development and population (Amudapuram Rao and Kalaga Rao, 2012). Beaudoin and Lawell (2017) finds that the elasticity of autonomous travel with respect to population is 0.47. Sweet (2013) suggests a positive association between large metropolitan areas and larger economies. Gas and diesel expenses shift the cost of driving and are thus correlated with car use. In their paper, Li, Hong and Zhang (2017) include freeway VMT and arterial VMT as variables affecting traffic. Data for these variables came from different sources. Data on population, freeway VMT, arterial VMT, diesel cost, and gas cost comes from UMR. GDP and median income are drawn from Census Bureau and US Bureau of Economic Analysis respectively. The summary statistics are presented in Table 3.

Table 3-Description of Control Variables and summary statistics

Variables	Description	Mean	Std. Dev.	Min	Max
Log_gdp	Log GDP in dollars	10.97	1.039	8.41	12.25
Log_popu	Log population	6.88	0.964	4.55	9.85
Log_income	Log median income	10.90	0.181	10.31	11.44
Log_comm	Log number of auto commuters(000)	6.17	0.925	3.78	8.69
Log_gas	Avg. diesel cost($/gallon)	.918	0.326	0.13	1.47
Log_diesel	Avg. gasoline cost($/gallon)	.100	0.371	0.19	1.59
Log_freeway	Log Free daily vehicle miles of travel(000)	9.02	1.10	6.06	11.84
Log_arterial	Log arterial street daily vehicle miles of travel(000)	9.11	0.95	6.90	11.74
Public_trans	Public transportation(excluding taxi)	68,791.9	288,765.4	195	2,932,789
No vehicles	No vehicle available	52,165.8	209,048.6	1716	2,131,145
Walked	Walk	23,929.29	57,663.42	882	543,733

Empirical framework

As mentioned earlier, isolating the causal effect of TNCs on traffic congestion is difficult due to the two-way causal relationship and uncontrolled confounding variable. To address the potential endogeneity, I deviate from the following fixed-effects regression model to limit selection bias and remove all time-invariant effects that vary across urban areas.

$$Traffic\ Congestionit = \alpha \text{TNCs}\ it + \beta \text{Controls}\ it + ci + \theta t + \epsilon it \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . (1)$$

Where the units of observation i index US metropolitan areas in year t to eliminate unobserved variables that are specific to each sample. The $TrafficCongestion_{it}$, the dependent variable, takes on one of the five performance measures in a metropolitan area i in year t.: TTI, CSI, hours of delay, excess fuel consumed, and congestion cost. $TNCs_{it}$ is specified as a dummy variable that takes the value of 0 or 1 or 2 to indicate the absence or presence of TNCs (Uber and Lyft) for urban area i in year t. Specifically, it takes a value of 1 for years that have officially launched Lyft or Uber, a value of 2 for years that have launched both Lyft and Uber, and a value of 0 for cities that do not have TNCs. $Controls_{it}$ indicates a set of control variables. α is the interested parameter; β is the parameter to be estimated. The metropolitan statistical area level fixed effects, *ci* and the year fixed effects, θ_t, were included in the regression to control for spatial and time-varying unobservable effects, respectively. ε_{it} represents the error term. The standard errors are clustered at the Geofips level.

Identification strategies

I seek to identify the causal effect of TNCs on traffic congestion by using two instrumental variables in order to account for any correlation between traffic congestion and the error term. The first instrument is a measure of whether individuals have smartphones.

Specifically, people must have a smartphone to participate in ride sharing services because users must book these services through a smartphone app. Therefore, a measure of whether an individual has a smartphone is likely to have a direct effect on TNC entry and is not likely correlated to traffic congestion. Hence, availability of smartphones is a reasonable instrumental variable for TNC entry. However, the instrument is limited by data availability. In particular, the data is not available for 2014. While not an ideal solution, the data used in the current study for the year 2014 is the average of the data from 2013 and 2015.

The second instrument is based on the measure of unemployment rate, maintained by the Bureau of Economic Analysis, following Li, Hong and Zhang (2017). The TNC self-employment model motivates people to participate in ride-sharing services; therefore, TNCs are likely to be in high demand in areas of high unemployment but uncorrelated with the error term. In addition, standard errors are also clustered at the Geofips level.

DID

The last identification strategy looks at the effects of TNCs by comparing changes in traffic congestion across the various urban areas with TNCs' entrance to changes in traffic congestion in the same time period in other American cities with no entrance, using the same dataset. Specifically, I estimate the impact of TNCs using the following difference-in-difference identification strategy.

$$Traffic\ Congestion\ it = \alpha Dit\emptyset + \beta Controls\ it\ + ci + \theta t + \epsilon it \ldots\ldots\ldots\ldots\ldots\ldots. (2)$$

where D_{it} represents the DID effect of TNCs on traffic congestion; $Controls_{it}$ is a vector of the explanatory variables; $\varnothing$ is the relative time dummy. Bertrand, Duflo and Mullainathan (2004) state the significance of using cluster-robust standard errors in DID settings. Accordingly, I cluster the standard errors at the Geofips level to eliminate the DID standard errors.

3. Empirical Results

The empirical results for each of the identification strategies are presented in Tables 4 through 6. The columns of Tables 4 through 6 present regression estimates including the set of control variables from Table 3 for all the different dependent variables from Table 2. Tables 4 and 5 present FE estimates and FE estimates including instrumental variables, respectively, while Table 6 presents DID estimates. In the analyses, I controlled for factors affecting traffic congestion and TNCs, removing the effect of the time trend and clustering the standard errors at the Geofips level.

The FE model results are presented in Table 4. The coefficient of TNCs has positive relations for all seven measures of congestion; however, the estimates are only marginally statistically significant. Moreover, there are no significant relations at the 1% level between TNCs and traffic congestion for the FE model. The results suggest that the entry of TNCs tends to increase traffic congestion, but found to have a statistically small or insignificant effect on traffic congestion. As discussed in the introduction, isolating the causal effect of TNCs on traffic congestion is challenging due to reverse causation and omitted variable bias. Furthermore, it is likely that the approach still suffers from endogeneity; as a result, this should not be interpreted as TNCs having no effect on traffic congestion.

Table 5 repeats the regression from Table 4, including the two instrumental variables for TNCs to account for possible endogeneity problems. For Table 5, the estimates of TNC entry on congestion measures (except for TTI) are significant and positive for all measures of congestion. Additionally, the estimates of the effect for delay time per auto, congestion cost per auto, excess fuel, and per auto are statistically more significant than the estimates for the FE model.

Table 6 presents the impact of TNCs across different types of traffic congestion using a difference-in-difference identification strategy as another method of handling the potential endogeneity. The coefficient of the interaction term indicates significant and positive effect for all the measures of traffic congestion, but smaller significant levels for delay time and excess fuel. These results imply that the entry of TNCs has a positive impact on traffic congestion, suggesting that the entry of TNCs increases traffic congestion. TNC entry can be seen to consistently increase traffic congestion for all measures of traffic congestion for all identification strategies.

Table 4-Results for the FE model

	Delay time	**Per auto**	**Cong _cost**	**Per auto**	**Excess _Fuel**
TNCs Entry	0.0049	0.005	0.005*	0.0049	0.0049
	(0.0025)	(0.0027)	(0.0025)	(0.0025)	(0.0025)
Log_gdp	0.3634***	0.3623***	0.3607***	0.3634***	0.3633***
	(0.0669)	(0.0636)	(0.0671)	(0.067)	(0.0669)
Log_income	0.2034*	0.1981*	0.2075*	0.2035*	0.2035*

	(0.0901)	(0.0902)	(0.0907)	(0.0903)	(0.0901)
Log_popu	0.0964	-0.2232	0.0994	0.0967	0.0966
	(0.1075)	(0.1140)	(0.1075)	(0.1076)	(0.1075)
Log_comm	0.2854**	-0.384***	0.2874**	0.2855**	0.2855**
	(0.1034)	(0.1095)	(0.1029)	(0.1035)	(0.1034)
Log_gas	0.0061	-0.0129	0.0086	0.0055	0.0063
	(0.0571)	(0.0616)	(0.0570)	(0.0573)	(0.0572)
Log_diesel	-0.0364	-0.0190	-0.0335	-0.0362	-0.0365
	(0.0787)	(0.0801)	(0.0764)	(0.0789)	(0.0788)
Log_freeway	-0.0109	-0.0099	-0.0111	-0.0113	-0.011
	(0.016)	(0.0174)	(0.0159)	(0.016)	(0.0159)
Log_arterial	0.0299	0.0282	0.0315	0.0308	0.0299
	(0.0241)	(0.0259)	(0.0242)	(0.0241)	(0.0240)
Public_trans	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No vehicles	-0.0000**	-0.0000*	-0.0000**	-0.0000**	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Walked	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	567	567	567	567	567
R^2	.8321	.6037	.4541	.4540	.8322
(Prob>F)	0.000	0.000	0.000	0.000	0.000

Notes: Robust standard error in parentheses; clustered by Geofips.

(Significance levels: *: p<0.05, **: p<0.01, ***: p<0.001)

Negative sign indicates a decline in traffic congestion;

positive sign indicates negative contribution to traffic congestion

Table 5-Results for the IV model

	Delay time	**Per auto**	**Cong _cost**	**Per auto**	**Excess _Fuel**
TNCs Entry	0.1352**	0.1007*	0.1091*	0.0899*	0.1739***
	(0.0482)	(0.0438)	(0.0427)	(0.0363)	(0.0517)
Log_gdp	0.0633	0.1208	-0.0041	0.0325	-0.0260
	(0.1364)	(0.1224)	(0.1013)	(0.0856)	(0.1349)

Log_income	0.1172	0.0579	0.124	0.0257	0.0296
	(0.2787)	(0.23)	(0.2648)	(0.2056)	(0.3336)
Log_popu	0.1455	0.3920	0.3224	0.5357	0.5678
	(0.6204)	(0.4697)	(0.6007)	(0.4245)	(0.7257)
Log_comm	0.2924	-0.7989	0.2028	-0.8594*	-0.0752
	(0.63016)	(0.48618)	(0.60873)	(0.43697)	(0.75197)
Log_gas	-0.53396	-0.65200	-0.59162	-0.59225	-1.00175
	(0.72122)	(0.63941)	(0.67792)	(0.57152)	(0.89140)
Log_diesel	0.80182	0.78138	0.67938	0.66202	1.09103
	(0.74037)	(0.68154)	(0.68876)	(0.60236)	(0.82702)
Log_freeway	0.09229	0.08558	0.10018	0.11819	0.04602
	(0.11155)	(0.09979)	(0.09511)	(0.08128)	(0.12441)
Log_arterial	0.51784***	0.40486***	0.46655***	0.34706**	0.50588**
	(0.14044)	(0.12243)	(0.13826)	(0.12729)	(0.18174)
Public_trans	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No vehicles	-0.000	-0.000*	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Walked	0.00001	0.000	0.00001*	0.00001	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.00001)
N	295	295	295	295	295
R^2	.9578	.6441	.9587	.6306	.9275
(Prob>chi2)	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Robust standard error in parentheses; clustered by Geofips.

(Significance levels: *: *p*<0.05, **: *p*<0.01, ***: *p*<0.001)

Negative sign indicates a decline in traffic congestion;

positive sign indicates negative contribution to traffic congestion

Table 6-Results for DID model

	Delay time	**Per auto**	**Cong _cost**	**Per auto**	**Excess _Fuel**
TNCs Entry	0.0101*	0.0091*	0.0089*	0.0089*	0.0147**
	(0.0041)	(0.0037)	(0.0037)	(0.0037)	(0.0049)
Log_gdp	0.3645***	0.3636***	0.3662***	0.3661***	0.378***

	(0.0633)	(0.0671)	(0.067)	(0.0669)	(0.0835)
Log_income	0.195*	0.2033*	0.1994*	0.1995*	0.2681*
	(0.0905)	(0.0913)	(0.0908)	(0.0907)	(0.1075)
Log_popu	-0.23*	0.0932	0.0906	0.0906	0.0835
	(0.1132)	(0.1075)	(0.1075)	(0.1074)	(0.1335)
Log_comm	-0.373***	0.2973**	0.2952**	0.2952**	0.311*
	(0.1073)	(0.1023)	(0.1028)	(0.1027)	(0.1304)
Log_gas	-0.0132	0.0089	0.0058	0.0066	0.0281
	(0.0617)	(0.0573)	(0.0575)	(0.0574)	(0.0820)
Log_diesel	-0.0153	-0.0309	-0.0337	-0.034	0.0649
	(0.0799)	(0.076)	(0.0785)	(0.0784)	(0.0873)
Log_freeway	-0.0114	-0.0123	-0.0125	-0.0121	0.0045
	(0.0176)	(0.0162)	(0.0163)	(0.0163)	(0.0215)
Log_arterial	0.0303	0.0338	0.0331	0.0322	0.0196
	(0.0263)	(0.0247)	(0.0246)	(0.0246)	(0.0356)
Public_trans	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No vehicles	-0.000*	-0.000**	-0.000**	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Walked	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	567	567	567	567	567
R^2	.6058	.4557	.4555	.8327	.7218
(Prob>F)	0.000	0.000	0.000	0.000	0.000

Notes: Robust standard error in parentheses; clustered by Geofips.

(Significance levels: *: p<0.05, **: p<0.01, ***: p<0.001)

Negative sign indicates a decline in traffic congestion;

positive sign indicates negative contribution to traffic congestion

Robustness check

Eighty-one percent of the nation’s total cost associated with traffic congestion, such as delays and fuel consumption, was expected from densely populated areas (Cortright, 2010).

Nearly 70% of Uber and Lyft ridership is concentrated in nine large and densely populated metropolitan areas, according to Schaller (2018). Following Yelowitz (1995), this section provides a third dimension, population group, in addition to urban area and year of TNC entry. The triple-differences model generates additional insightful analysis to the general DID analysi (Angrist and Pischke, 2008).

Table 7 provides the empirical results, in which the sample size is restricted by those metropolitan areas with populations over one million, classified as "large" from the dataset used for the main analysis. The results are found to be significant and positive in terms of the effect of TNCs on delay time, congestion cost, and excess fuel among largely populated areas. The significance levels of the estimates indicate that the TNCs become problematic for the trend of traffic congestion. Moreover, the coefficients on TNCs are larger in magnitude than the aggregate data.

Table 7- Urban Areas with groups of "large" population

	Delay time	**Per auto**	**Cong _cost**	**Per auto**	**Excess _Fuel**
TNCs Entry	0.01467**	0.01419*	0.01467**	0.01471**	0.01467**
	(0.00415)	(0.00541)	(0.00417)	(0.00413)	(0.00415)
Other controls	Y	Y	Y	Y	Y
N	180	180	180	180	180
R2	.9048	.7213	.6501	.6481	.9048
(Prob>F)	0.000	0.000	0.000	0.000	0.000

Notes: Robust standard error in parentheses; clustered by Geofips.

(Significance levels: *: $p<0.05$, **: $p<0.01$, ***: $p<0.001$)

4. Conclusion

This paper reports on the findings of the causal impact of TNC entry on traffic congestion, which warrants further elaboration. I examined the roles of TNCs on different measures of traffic congestion, extending the analysis regressions to reduce the endogeneity bias. To confirm that the increase in traffic congestion was caused by TNCs rather than other factors, I made use of instrumental variables, employed a difference-in-difference identification strategy while removing time-invariant effects that vary across urban areas, and included a set of explanatory variables.

The empirical results for all key coefficients of interest were positive for all strategies, denoting that the arrival of TNCs generates more traffic congestion. To assess the robustness of the preceding results, I repeated the analysis using datasets that corresponded to those metropolitan areas classified as large instead of examining all metropolitan areas. In accordance with the findings in Tables 4 through 6, the results point to a significant and negative contribution to traffic congestion.

The findings may reveal some insights into the ongoing debate; however, as stated earlier, they have limitations in several dimensions given the limitations of available data. For instance, Uber was introduced for the first time in 2011 in San Francisco; however, it takes time for people to actually use such new types of services. This disproportionality may influence the representativeness of the entry of TNCs. Moreover, the main dataset from Texas A&M Institute aggregates at an annual level and covers only up to the year 2014. Thus, it is difficult to examine the long-term effects of TNCs. Lastly, identifying strong and valid instrumental variables that have a direct effect on the entry of TNCs but not on traffic congestion is extremely difficult.

While environmental factors are outside of the control, it would be interesting for future research to use a longer timespan's dataset of traffic congestion in the post-TNC time period and to use more representative TNC data.

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