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Bike-sharing systems and congestion: Evidence from US cities

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ABSTRACT

In the past decades, there has been a resurgence of public bike-sharing systems (BSSs). While it is claimed that social and environmental benefits are associated with the implementation of BSSs, few empirical studies have investigated the actual congestion reduction effect of BSSs on cities. To fill such gap, this paper aims to examine whether the launch of BSSs can reduce citywide congestion. With a panel dataset of 96 urban areas in the US from 2005 to 2014, we employed a difference-in-differences model with two-way fixed-effects panel regression. The results suggested that the introduction of BSSs shows a significant mixed impact on congestion in general: Larger cities get better off but richer cities get worse off. Such results are consistent with both subsample regression with propensity score matching and different congestion measures. Post-hoc analysis reveals that BSSs have a significant positive effect on reducing rush-hour congestion. Finally, implications, limitations, and future work directions are offered

1. Introduction

A resurgence of (public) bike-sharing systems (BSSs) has been witnessed around the world in the past decades. Although the idea of BSSs has been around for almost half a century, it is only recently that such systems have been strategized as sustainable transportation means worldwide. For example, public bike docking stations, which were hardly seen in Asia, Australia, and the Americas before 2008, have been a recognizable feature in many cities nowadays (Midgley, 2011). Indeed, the number of cities with a BSS has increased from 13 in 2004 to 855 as of 2014 (Fishman, 2016). While Europe continues pioneering BSSs and has begun to adopt a new generation of BSSs, North America is at an early stage but gains rapid growth of BSSs (Parkes et al., 2013). Most common BSS can be described as a public program, which offers bikes that can be picked up and returned at docking stations for free or a small fee across an urban area. Trips using BSSs are usually of short duration (e.g., 30 min). Contemporary internet and communication technologies (ICTs) are typically embedded into BSSs to facilitate program management and operation. For instance, smartphone apps are developed and provided to the end-user to enable bike check-out and return. The global positioning system (GPS) units are also adopted in some BSSs to track bike locations. Geographic information system (GIS) has also been introduced to monitor and allocate bikes across different docking stations.

Although the explicit goals of the introduction of individual BSSs may be different, BSSs are associated with social, environmental, and health benefits, including but not limited to congestion and emission reductions, flexible mobility, consumer financial savings, and positive health outcomes (Midgley, 2011; Shaheen et al., 2010). Despite above-mentioned benefits of BSS, there are at least two concerns about the effectiveness of the BBS functionality from previous studies. First, cycling itself rather than the BSS, in general, provides many of the benefits above (Handy et al., 2014; Pucher and Buehler, 2012). Although one of those objectives of BSSs is to promote cycling, such effect cannot be taken for granted. The improvement of bike lanes and the increase docking stations can also facilitate cycling activities. In other words, it may not be necessarily through the launch of BSSs to achieve such benefits. Second, the achievement of such benefits relies heavily on the effectiveness of BSSs. For instance, the benefits of mobility, financial savings, and health depend on the actual participation level of BSS users. The social and environmental benefits of congestion and emission reduction depend on the degree of modal shift from automobile to the real use of BSSs. In other words, the launch of BSSs may not be sufficient to achieve such positive outcomes. Although a few previous studies examined the environmental benefits associated with the BSS (DeMaio, 2009), very few empirical studies examined the effect of congestion reduction related to the introduction of the BSSs across the US. In a recent study, Hamilton and Wichman (2017) found that BSSs can reduce congestion at neighborhood scale in Washington, D.C. Therefore, we aim to expand the scope of cities and provide a high-level assessment of the relationship between the launch of BSSs and congestion through a difference-in-differences (DID) model that examined

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the congestion over ten years (2005–2014) in 96 urban areas in the US.

To our knowledge, this is the first comprehensive study to examine whether the launch of BSSs has an impact on congestion using DID. With the DID method, the two-way fixed-effect panel regression results indicate that the introduction of BSSs has significant mixed effects on congestion. Our results are robust to subsample regression with propensity score matching and different measures for congestion. Post-hoc analysis reveals BSSs have a significant positive impact on reducing peak-hour congestion. Based on our findings, policy implications are discussed. Next, we provide the background of BSSs and related literature in BSSs and congestion (Section 2) before introducing our data and empirical strategies with difference-in-differences methods along with robustness checks (Section 3). Section 4 presents the results. Finally, Section 5 discusses implications and limitations of this work.

2. Background and related work

In this section, we first briefly summarize the history of the four-generations of BSSs. Second, we present a retrospective of empirical works dealing with the benefits and concerns of BSSs.

2.1. A brief history of BSSs

The world's first BSS, namely the "White Bike", was launched in Amsterdam in 1965. It failed relatively quickly due to theft and vandalism, as those bikes were not equipped with any security features (DeMaio, 2009). According to Parkes et al. (2013), this also marked the first-generation of BSSs, which was characterized by no payment or security functionalities. Established in Copenhagen in 1995, the second-generation of BSSs was upgraded with a coin deposit system. However, it still faced the problem of theft (DeMaio, 2009). The emergence and prosperity of ICTs have enhanced the security functions and reduced the management risk of BSSs by enabling the tracking of bicycles and electronic payment systems. With fixed docking stations, ICT-enabled BSSs are also recognized as the third-generation of BSSs (Shaheen et al., 2013). Meanwhile, there is a growing public policy interest in the benefits associated with BSSs (Midgley, 2011; Shaheen et al., 2010). Consequently, practices on the third-generation of BSSs have recently increased dramatically around the world. From 2004 to 2014, cities with BSSs have surged from 13 to 855 (Fishman, 2016). Cities across the globe have adopted different operation and pricing schemes. For example, in Netherlands, there is a single nationwide bike sharing program named "OV-fiets" with the requirement of membership subscription and "OV-chipkaart"—a contactless smart card. In London, Barclays and then Santander have sponsored the Transport for London for its BSSs, in which the first 30-min is free with a payment of 2 GBP access fee by credit card. In North America, a Montreal-based company named PBSC Urban Solutions has provided integrated BSS solutions (including bikes, pay stations, locking systems and smartphone applications) to a number of cities, such as Montreal and Toronto in Canada, Boston, New York City and Washington, D.C. in US, and Guadalajara, and Toluca in Mexico. In South America, municipal governments, such as Buenos Aires, Argentina, Rio de Janeiro, Brazil, and Quito, Ecuador, partner with local commercial firms to operate citywide BSSs. The fourth-generation of BSSs is emerging now; it includes features such as dockless stations, better integration with public transit systems, and power assistance (Parkes et al., 2013). In June 2017, Urbo began to operate dockless bike-sharing programs in Ireland and across Europe. In China, the largest two BSS operators (i.e., Mobike and Ofo) have also adopted dockless stations. While Mobike became the world's biggest operator of BSSs in December 2016, Ofo had secured over 20 million users by March 2017 (http://www.reuters.com/article/us-china-ofo-fundraising-idUSKBN1683C9). For a more detailed overview of recent developments in BSSs, please see the review papers conducted by Fishman et al. (2013) and Fishman (2016).

2.2. Purported benefits of BSSs

There are a number of purported social, environmental, and health benefits of BSSs. Shaheen et al. (2010) and Shaheen et al. (2013) summarized as (1) congestion, emission, air pollution, and noise reductions; (2) flexible mobility, transportation connection improvement; (3) health promotion; and (4) consumer financial savings. Many of the benefits mentioned above count on the assumption that the implementation of BSSs has encouraged users to switch to BSSs for trips previously made by car. However, empirical evidence has not reached a consensus about whether such assumption is indeed based on reality (Midgley, 2011).

The first strand of studies shows general agreement with the assumption that the launch of BSSs has demonstrated an increase in overall cycling activities in urban areas. For example, after launching the BSSs, the percentage of trips made by bike grew by 1% from 2005 to 2007 in Barcelona, by 1.5% from 2001 to 2007 in Paris, and by 1.5% from 1995 to 2006 in Lyon (Garcia-Palomares et al., 2012). Furthermore, a study of the BSS (OYBike) in London revealed that 40% of users shifted from automobiles to the BSS (Noland and Ishaque, 2006). However, Pucher et al. (2010) argued that such results were confounding because, despite the fact that cycling has increased in cities since the introduction of the BSSs, the growth of bike mode share might be because of the overall improvement of biking facilities. Nevertheless, DeMaio (2009) explicitly showed that the BSS in Montreal had successfully reduced greenhouse gas emissions by over 1300 tons since its inception in 2009. A recent study by Hamilton and Wichman (2017) revealed that BSSs reduced congestion of neighborhoods in Washington, D.C. Moreover, studies indicate that the increased cycling behaviors due to the execution of BSSs are associated with significant improvements in fitness and public health, such as reduced risks of heart disease and cancer (Cavill et al., 2006; Rojas-Rueda et al., 2011; Shaheen et al., 2010). In summary, most evidence that BSSs can increase cycling behaviors is limited to individual cities.

The second strand of studies seems to reject the assumption that the implementation of BSSs has encouraged users to switch to BSSs for trips previously made by car for varied reasons. First, many users of BSSs or bikes use them for leisure but not for commuting. For example, Noland et al. (2011) conducted a statewide study and revealed that most people use bikes for recreational purposes in New Jersey, USA. In other words, BSSs promoted some trips which would not have been made in the absence of BSSs (Ahillen et al., 2016). Furthermore, López-Valpuesta and Sánchez-Braza (2016) found that in Seville, Spain, BSSs and private bikes were two complementary modes of transport and the mean distance of trips made by the former was 700–800 m shorter than that made by the latter. Second, there are concerns that the launch of BSSs and other bike facilities may just reinforce the behavior of existing bicyclists but not recruit new members who would switch transport mode to bikes. Buck et al. (2013) found that BSS members are not frequent bike-share users, as 21% female and 13% male members in Washington, DC, reported no rides in a typical month. Schoner et al. (2015) showed that bike lanes are more likely to attract existing bicyclists to a neighborhood than to encourage non-bikers to shift transport modes. More recently, Mitra et al. (2017) reported that after the redevelopment of bike facilities in downtown Toronto, Canada, young people were still less likely to switch from a car trip to a bike trip. Third, some scholars are concerned about the negative externalities associated with BSSs. The launch of a BSS is usually accompanied by certain changes in bike facilities. For example, the installation of docking stations occupies public space; prescribing bike lanes and increasing the width of bike facilities reduces lane space for automobiles, which consequently impacts the level of service of a road (Burke and Scott, 2016). In a nutshell, many users of BSSs may regard BSSs at best as an adjunct to their primary transport mode, and facilities associated with BSSs may impose adverse consequences. Such inconsistent arguments in the effect of BSSs on road congestion call for further empirical studies to explore actual performances of BSSs across US cities.

Importantly, although cities worldwide have implemented BSSs to propel utilization of bikes, the success of BSSs depends on how the demand for the BSS from the end-user would be satisfied (Frade and Ribeiro, 2014; Wolf and Seebauer, 2014). After all, for end-users, the primary perceived benefits of BSSs are convenience and low travel cost (Fishman et al., 2013). In short, there has not been an agreement so far about whether the launch of BSSs has promoted the conversion of trips previously made by automobile to BSSs. Because of the inconsistency in the role of BSSs in the shift of transportation means, and the lack of empirical studies that investigate the effect of BSS on congestions reductions across the US, we conducted an empirical study to find the relationship between the launch of BSSs and congestion using data from 96 urban areas across US from 2005 to 2014. The following section introduces the data and methods employed in this study.

3. Data and methods

3.1. Data and study areas

Our data are mainly from four sources. First, congestion-related data were obtained from the Texas A & M Transportation Institute (https://tti.tamu.edu/), which combines speed data from INRIX (http://inrix.com/) and the volume and roadway inventory data from the Highway Performance Monitoring System from the US Federal Highway Administration (FHWA). It describes congestion in a consistent way, allowing for comparisons among different urban areas. INRIX provides real-time traffic data so that "real" rush hour speeds of fleets are measured, and overnight speeds are used to provide free-flow speeds. It contains (1) quarterly congestion statistics from 52 US urban areas from the fourth quarter of 2008 to the second quarter of 2015; (2) yearly congestion statistics from 100 US urban areas and San Juan, Puerto Rico, from 1982 to 2014. Second, socioeconomic profiles and urban travel characteristics across different urban areas were acquired from American Community Survey (ACS). Third, weather and climate data were obtained from the National Climatic Data Center, National Oceanic and Atmospheric Administration (NCDC-NOAA). Lastly, we manually consolidated information regarding the launch time of BSSs in the 100 US urban areas from the official website of BSSs and mass media. San Juan, PR was excluded to control for the potential political heterogeneity between Puerto Rico and the 50 US states.

We decided to use the yearly congestion statistics from the 100 US urban areas because, on the one hand, these statistics not only contain a considerable sample size; on the other hand, the exact launch month of BSSs is sometimes either missing or hard to validate. Given that the first BSS was initiated in 2007 among the 100 urban areas and most data from ACS are only available since 2005, the period from 2005 to 2014 was selected for this study. As there are four urban areas (i.e., Albany-Schenectady (NY), Honolulu (HI), Las Vegas-Henderson (NV), and Louisville-Jefferson County (KY-IN)) without complete time-series data covering the ten years' period, our final sample include 96 urban areas, which results in a total number of 960 observations. Fig. 1 illustrates the geographical distribution of the 35 urban areas with BSSs and the 61 urban areas without BSSs.

3.2. DID with two-way fixed-effects panel regression

The DID approach was employed to evaluate the impact of BSS launches on congestion in the 96 urban areas in the US for 2005–2014. DID is a well-established method and has been applied to transportation studies (e.g., Grimes and Young, 2013; Hurst and West, 2014, and Combs, 2017). Conceptually, DID assesses the impact of the implementation of BSSs on congestion by calculating double differences, one over time (before and after the launch of BSSs) and one across urban areas (urban areas with BSSs and those without BSSs). We used a DID regression specified as the following two-way fixed-effects model (Eq. 1):

$$Y_{it} = \gamma Z_{it} + \beta X_{it} + \theta_i + \delta_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the congestion of the ith urban area and in the year of t, Z_{it} is the dummy variable of BSS entry to be assessed in the ith urban area and in the year of t, and X_{it} is a suite of time-varying control variables of the ith urban area and in the year of t. θ_i is the fixed-effect control variable for time-invariant omitted variables for the ith urban areas, δ_t is the fixed-effect control variable for trends in urban areas in the year of t. ε_{it} is the random error term in the ith urban area and in the year of t.

In the DID specification above, γ is the key parameter, which measures the difference between the average change in congestion for the treatment group (i.e., urban areas with BSSs) and the average change in congestion for the control group (i.e., urban areas without BSSs). It is also known as the average treatment effect on the treated (ATET) (Eq. 2)

$$\gamma = E(Y_1^T - Y_0^T \mid T_1 = 1) - E(Y_1^C - Y_0^C \mid T_1 = 0) \quad (2)$$

where ${Y_t}^T$and ${Y_t}^C$ are average congestion for urban areas in the treatment group and the control group in time t, respectively. $t = 0$ refers to the period before BSS entry, and $t = 1$ refers to the periods after BSS entry. $T_1 = 1$ refers to treatment (the presence of BSSs in the urban areas), and $T_1 = 0$ refers to controls (the lack of presence of BSSs in the urban areas) at $t = 1$.

The DID approach has the following advantages. First, we do not need to consider all the variables that affect congestion because subtracting the difference before entry of BSSs in congestion from after entry of BSSs eliminates selection bias under the condition that this unobserved heterogeneity is time invariant. Second, it allows us to quantify how much of the change in congestion is ascribed to the launch of BSSs as well as how much of that would have happened despite the introduction of BSSs.

Nevertheless, one assumption of DID approach is that both the treatment group and the control group would have similar trends before treatment. Additionally, one concern about two-way fixed-effect panel regression model is that the treatment groups may differ in ways that would affect their trends over time. To mitigate such concerns about treatment heterogeneity and correct model specification, Ho et al. (2007) proposed matching with propensity scores (a.k.a., propensity score matching, PSM). More recently, Ferraro and Miranda (2017) found the combination of panel data with PSM is more likely to approximate a randomized controlled trial than applying a single design. Therefore, our robustness check started with constructing a subsample with only "matched data", which includes all urban areas within the treatment group and those urban areas in the control group that are most observationally similar to the urban areas in the treatment group. Following Hamilton and Wichman (2017), we used propensity scores to create the subsample and re-ran the regression model with the subsample.

Additionally, we conducted the following robustness checks. First, we used the Augmented Dickey-Fuller test to test the stationarity of congestion measures with the first order of lag. If it failed to reject the null hypothesis of the unit root, the first order difference of congestion measures needs to be taken to stabilize the time-series. Second, we checked the specification of our two-way fixed-effects model using the Hausman test, where the null hypothesis is that panel regression with random effects is more appropriate than that with fixed effects. Third, we applied the Breusch-Godfrey test for potential serial correlation (temporal correlation) of error terms within each urban area and the Breusch-Pagan test for possible inconstant variance of error terms (heteroscedasticity). If either serial correlation or heteroscedasticity is found, robust standard errors should be reported (Arellano, 1987). Fourth, we utilized an additional congestion measure to check the consistency of our results. Lastly, a post-hoc analysis was included to explore the role of BSSs in rush-hour congestion further.

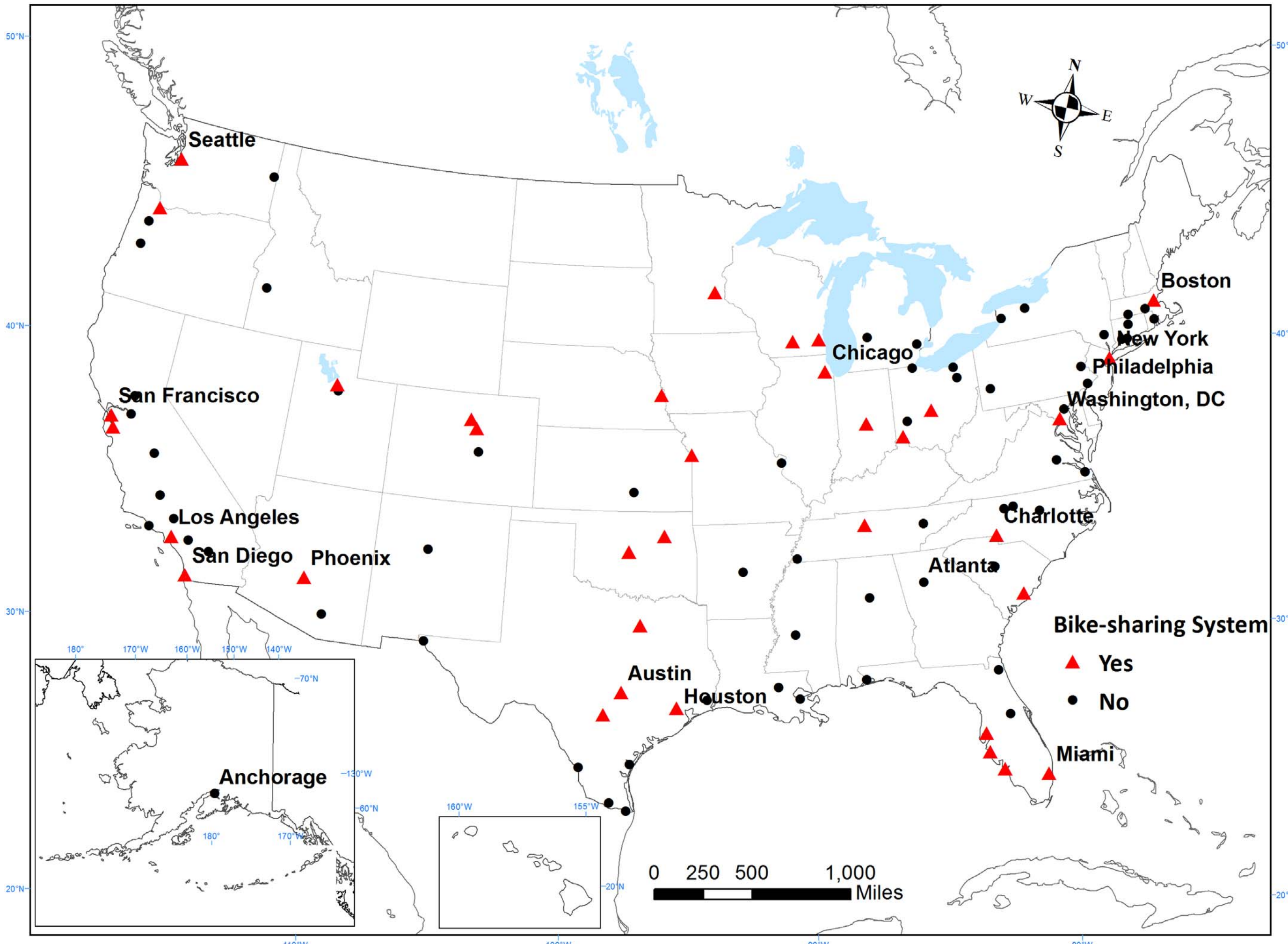

Fig. 1. Bike-sharing systems (BSSs) in US urban areas, 2005–2014. Yes = 35; No = 61. Selected cities are labeled to the top right of the corresponding cities. The base map is provided by ESRI as a courtesy.

3.3. Variables

We list all variables along with their sources and descriptions applied in this study in Table 1. Our explanatory variable of interest is the interaction term (Z_{it} in Eq. 1) between the treatment group dummy and post-treatment dummy (*BSS* = *Treated* * *Post*), which is a dummy variable (1 = the launch of a BSS) representing the entry of BSSs. A suite of control variables (X_{it} in Eq. 1) are obtained from three difference data sources, including the UMS, the ACS, and the NCDC-NOAA. From the UMS, the total population in thousands (*Population*) is used to proxy for the size of the urban area. Second, the percentage of autocommuters (*Autocommuter*) is computed as the total number of autocommuters divided by the total population. Third, the average arterial street daily thousand miles of travel (*VMT*) is gathered. An arterial street often delivers traffic between different urban centers and from distributor roads (i.e., low-to-moderate-capacity roads which moves traffic from local streets to arterial roads) to freeways. *VMT* is populated as the average daily traffic of a section roadway multiplied by the length of that section of roadway. From the ACS, the median income in USD (*Income*) and median age (*Age*) were obtained to control for socioeconomic profiles; the percentages of workers who use public transport (excluding taxi cabs) to work and bike to work (*Public_Transport*, and *Bicycle*, respectively) are added to control for urban travel behaviors. From the DCDC-NOAA, average precipitation (*Precipitation*) and temperature (*Temperature*) data were obtained to control for urban weather and climate factors.

For the dependent variables (Y_{it} in Eq. 1), we have included two different measures of congestion from the Urban Mobility Scorecard (UMS) product, namely the total annual excess fuel consumed in a thousand gallons (*AEFC*), the annual hours of delay per autocommuter (*AHD_AC*). The total annual excess fuel consumed in a thousand gallons (*AEFC*) is calculated as the difference in fuel consumption during congested conditions and free-flow conditions. The annual hours of delay per autocommuter (*AHD_AC*) is calculated as the summation of the total peak period delay divided by the total of autocommuters and the total remaining period delay divided by the total population. *AHD_AC* includes off-peak delay on purpose, as it also takes delays during other times of the weekdays and the weekends into consideration. While both measures represent general congestion conditions, we applied the commuter stress index (*CSI*) in the post-hoc analysis as proxy for rush-hour congestion. The commuter stress index (*CSI*) is the travel time in the peak directions during the peak periods divided by the free-flow travel time, which indicates the congestion of daily work trip experienced by each commuter. Peak periods are defined as the morning peak hours (6 a.m. to 10 a.m.) and the evening peak hours (3 p.m. to 7 p.m.). CSI is unitless, which allows for comparing trips of different distances to estimate excess work trip travel time compared to free-flow conditions. Changes in *CSI* are calculated by subtracting 1.0 from the *CSI* values; therefore, such changes reflect the differences in extra travel time rather than the numeric number of *CSI*. For example, an increase of *CSI* from 1.1 to 1.2 is 100% (i.e., extra travel time of 20% compared to 10%). Detailed algorithms of congestion measures can be found in the

Table 1
Summary of variables.

Variable	Unit	Description	Data source[a]
Explanatory			
Treated	N/A	The treatment group dummy (0 = No, 1 = Yes)	Manually collected by the authors
Post	N/A	The post-treatment dummy (0 = No, 1 = Yes)	Manually collected by the authors
BSS	N/A	The entry of bike-sharing system, *Treated* * *Post* (0 = No, 1 = Yes)	Calculated by the authors
Control			
Population	N/A	Population (in thousands)	USM
Autocommuter	N/A	Total autocommuters divided by total population * 100%	USM
VMT	Thousand Miles	Arterial street daily mileage of travel	USM
Income	USD	Median Income	ACS
Age	N/A	Median age	ACS
Public_Transport	N/A	Percentage of workers use public transportation (excluding taxi cabs) to work	ACS
Bicycle	N/A	Percentage of workers use bike to work	ACS
Precipitation	Inches	Average precipitation	NCDC-NOAA
Temperature	Degrees Fahrenheit	Average temperature	NCDC-NOAA
Dependent variable			
AEFC	Thousand gallons	Annual excess fuel consumed	USM
AHD_AC	Hours per autocommuter	Annual hours of delay per autocommuter	USM
CSI	N/A	Commuter stress index (travel time index calculated for only the peak direction in each peak period)	USM

[a] UMS = Urban Mobility Scorecard (https://mobility.tamu.edu/ums/); ACS = American Community Survey (https://www.census.gov/programs-surveys/acs/); NCDC-NOAA = National Climatic Data Center, National Oceanic and Atmospheric Administration (https://www.ncdc.noaa.gov/).

official website of UMS (https://mobility.tamu.edu/ums/congestion-data/). Temporal dynamics of these three measures of congestion are plotted in Fig. 2.

4. Results

The descriptive statistics of all variables are shown in Table 2. Except for the dummy variables (i.e., *Treated*, *Post*, and *BSS*), all variables were log-transformed before regression. Results of the DID approach with the two-way fixed-effects (i.e., year and urban area fixed effects) panel regression model are shown in Table 3. We progressively added the explanatory variables for the launch of bike-sharing systems, control variables for socioeconomic, travel behavior, and climate conditions, and finally those interaction terms (Model 1 to Model 3 in Table 3). Model 3 represents our full model. From Model 1 to Model 3, the adjusted R^2 increases from 0.117 to 0.519.

To further confirm our full model specification, we have checked the following statistical tests. First, the Augmented Dickey-Fuller Test with the first order of lag is significant ($p < 0.01$), indicating that the time-series are stationary so that there is no need to take the first order difference of the dependent variable. Second, the Hausman test is significant ($\chi^2 = 150$, $p < 0.01$), suggesting that panel regressions with two-way fixed effects are more appropriate than those with random effects. Third, we reported robust standard errors in Table 3 to control for potential problems of serial correlation or heteroskedasticity.

In Model 3, it shows the entry of bike-sharing systems has mixed impacts on congestion. On the one hand, it mitigates the positive role of the population on congestion. Urban areas with the launch of BSSs, a 1% increase in total population will result in 0.0264% less congestion compared to those without BSSs. In other words, BSSs benefit larger cities more than they do to smaller ones regarding congestion reduction. On the other hand, they strengthen the positive role of median income to congestion. Specifically, with the presence of BSSs, a 1% increase in median income will lead to 0.1021% more congestion of the urban area compared to those without BSSs. In another word, richer cities get worse off by introducing BSSs regarding congestion. Also, in Model 4, we re-estimated Model 3 using only matched samples, which are derived from PSM. The results are consistent with those in Model 3, with the slightly different magnitude of the beta coefficients for the interaction terms. The preprocessing of data with PSM also increases the adjusted R^2 by 20% (from 0.519 to 0.625).

Furthermore, Model 3 was re-estimated by changing the congestion measure from the annual excess fuel consumed (*AEFC*) to the annual hours of delay per autocommuter (*AHD_AC*) in Model 5 (Table 4). The results are consistent with those in Model 3 (Table 3). Lastly, as a post-hoc analysis, we changed the dependent variable to the commuter stress index (*CSI*), which proxies the congestion during rush-hour in peak directions (Model 6). Model 6 reveals that in addition to the mixed moderating effects, the launch of BSSs has a significant direct impact on reducing rush-hour congestion. In the next section, we will discuss such findings elaborately and provide implications based on the empirical results.

5. Discussions and conclusion

With a difference-in-differences model with two-way fixed-effects panel regression, this study has revealed that the launch of BSSs has statistically significant mixed effects on congestion based on the 96 US urban areas, 2005–2014. Such findings are robust to regression with matched subsamples from propensity score matching and different measures of congestion. Such results have the following policy and management implications.

First, we found that BSSs benefit larger cities more than smaller ones in congestion reduction. Using the measure of excel fuel consumption as a proxy for congestion, this finding shows alignment with previous studies that BSSs universally reduce driving and taxi use in almost every city (Martin and Shaheen, 2014; Shaheen et al., 2013). Additionally, our finding suggests conditioning on other covariates, a 1% increase in the population of cities without BSSs is associated with 0.6863% increase in congestion; however, a 1% growth in the population of cities with BSSs is associated with 0.0264% less increase in congestion. Compared to smaller cities, larger cities usually have more robust public transport systems, which offers more routes and frequent services. As many of docking stations are located near public transport stops, BSSs encourage multimodal transport by providing connections with public transport systems. Therefore, in larger cities, BSSs may facilitate substituting short-distance trips which would be otherwise made through cars. In rush hours, it can divert traffic and reduce transportation congestion. Conversely, in smaller cities, where there are fewer routes and sparse services, BSSs may serve as complements to

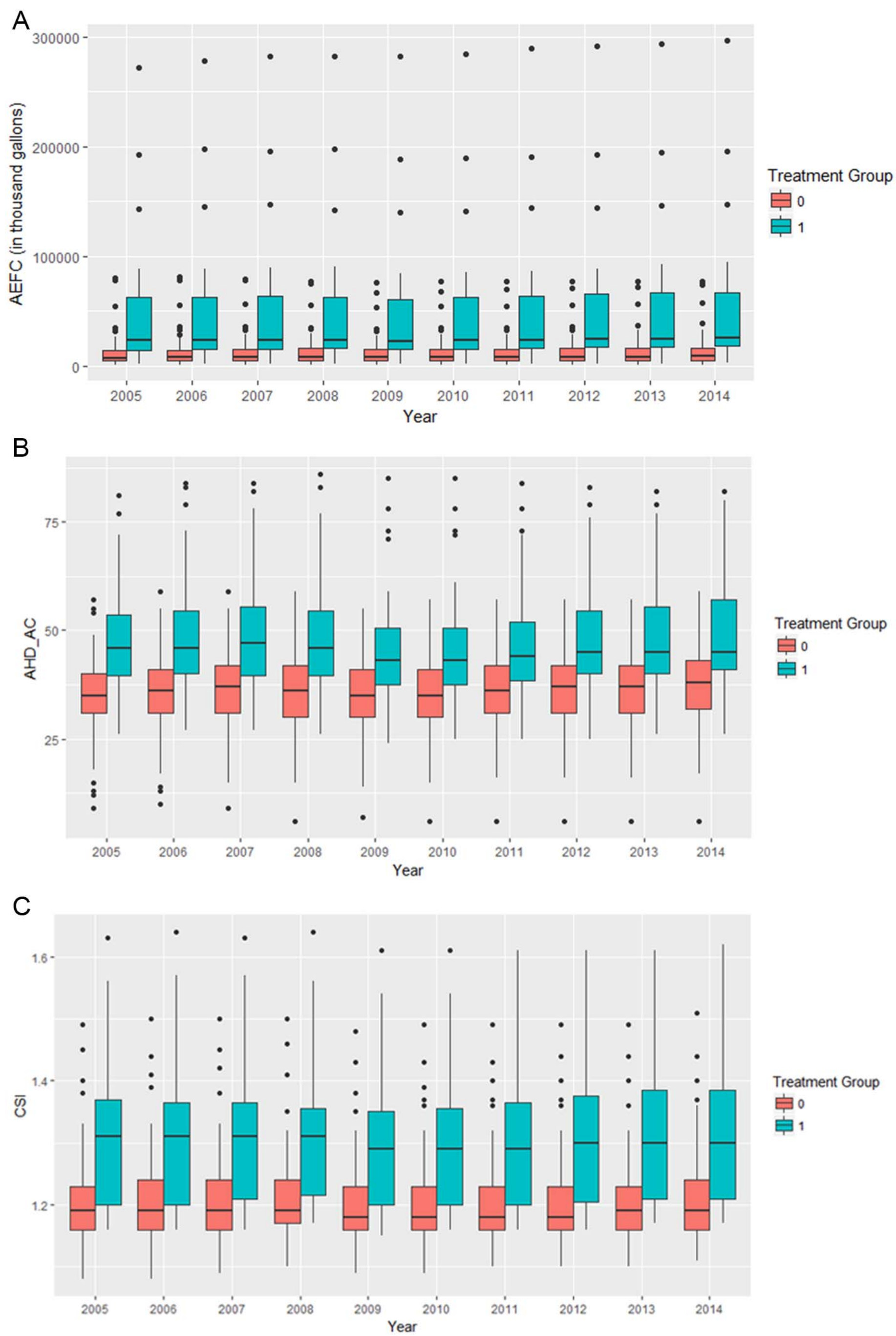

Fig. 2. Plots of congestion measures 2005–2014. (A) Annual excess fuel consumed (AEFC); (B) annual hours delay per autocommuter (AHD_AC); (C) commuter stress index (CSI).

public transit by providing connections between different transit stops. Such findings also resonate Hamilton and Wichman (2017)'s study, where they found DC's Capital Bikeshare has a positive role in traffic congestion reduction.

Additionally, we observe a sublinear scaling relationship between total population and congestion at US urban area level. Although more populated urban areas are inevitably associated with more congestion than less populated ones, the rate at which congestion increases is slower than that of the total population. The launch of BSSs allows such "increase" even slower. As the logarithm was taken for all non-dummy variables, those beta coefficients can be interpreted in favor of elasticity in economics, and we do find the economies of scale, as defined by Bettencourt et al. (2007). Relatedly, larger cities are associated with less per capita congestion, as reflected in Model 5 where congestion is measured by annual hours delay per auto commuter and in Model 6 which indicates rush-hour congestion in peak directions experienced by each commuter.

Second, richer cities tend to get worse off with the introduction of BSSs. Richer cities usually have greater ownership of private cars and more luxury cars. One possible explanation is that the launch of BSSs sometimes encourages extra trips which would not be made without such facilities (Ahillen et al., 2016). With a greater private car ownership, people in richer cities may be more likely to use cars as connectors to those "extra trips", resulting in more traffic on the road.

Third, as the post-hoc analysis indicates, BSSs have a direct effect on reducing congestion during rush hours, which may imply a modal substitution, where people reduce car and bus use as a result of BSSs. Such finding is consistent with bike-share member surveys (e.g., Buck et al., 2013; Shaheen et al., 2013), although these studies find the size of the modal substitution effect differs both across cities and within

Table 2
Descriptive statistics of variables (N = 960).

Variable	Mean	SD	Min	Max
Explanatory				
Treated	0.36	0.48	0	1
Post	0.8	0.4	0	1
BSS	0.29	0.45	0	1
Control				
Population	1700.15	2539.12	105	19,040
Autocommuter	49.42	4.02	26.96	55
VMT	15,086.38	19,549.85	988	125,800
Income	25,965.48	4329.22	12,345	42,376
Age	36.06	3.54	23.5	52.5
Public_Transport	3.56	4.32	0.1	32.7
Bicycle	0.72	1.16	0	11
Precipitation	37.09	19.22	0.27	138.7
Temperature	59.03	8.59	43.3	77.4
Dependent variable				
AEFC	25,522.23	40,325.28	644	296,701
AHD_AC	39.88	13.18	6	86
CSI	1.24	0.1	1.08	1.64

Table 3
The effect of bike-sharing systems (BSSs) on congestion.

Model	(1)	(2)	(3)	(4)
Sample	Full	Full	Full	Matched only
Post	0.0641	− 0.0005	0.0024	− 0.0213*
	(0.0127)	(0.0101)	(0.0101)	(0.0099)
BSS = 1	0.0166	0.0047	− 0.8422	− 0.7571
	(0.0163)	(0.0124)	(0.4292)	(0.4737)
Control				
Population		0.7032***	0.6863***	0.6498***
		(0.0590)	(0.0582)	(0.0576)
Autocommuter		0.4407***	0.3636**	0.2776
		(0.1301)	(0.1302)	(0.1437)
VMT		0.0631	0.0660	0.1250***
		(0.0404)	(0.0413)	(0.0345)
Income		0.4354***	0.4130***	0.4292***
		(0.0508)	(0.0561)	(0.0502)
Age		− 0.1940	− 0.1466	0.0163
		(0.1945)	(0.2003)	(0.1214)
Public_Transport		0.0006	− 0.0011	0.0057
		(0.0084)	(0.0083)	(0.0083)
Bicycle		− 0.0010	− 0.0010	0.0112
		(0.0015)	(0.0015)	(0.0061)
Precipitation		− 0.0045	− 0.0041	− 0.0034
		(0.0063)	(0.0062)	(0.0050)
Temperature		0.0497	0.0648	0.1243**
		(0.0570)	(0.0560)	(0.0458)
Interaction				
BSS * Population			− 0.0264***	− 0.0215**
			(0.0068)	(0.0067)
BSS * Income			0.1021*	0.0916*
			(0.0433)	(0.0456)
Year fixed effects	Yes	Yes	Yes	Yes
Urban area fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.117	0.509	0.519	0.625
F-statistic	112.303***	99.689***	87.975***	78.605***
Observations	960	960	960	560

Congestion is measured by annual excess fuel consumed (*AEFC*). The treatment group dummy (*Treated*) was dropped due to multicollinearity. The natural logarithm was taken for all non-dummy variables. Heteroskedasticity consistent coefficients are reported in parenthesis.
Significant codes: '***' 0.001, '**' 0.01, '*' 0.05.

Table 4
Regression results of robustness check and post-hoc analysis.

Model	(5)	(6)
Dependent variable	AHD_AC	CSI
Post	0.0026	0.0009
	(0.0108)	(0.0016)
BSS = 1	− 0.8841	− 0.2873**
	(0.4594)	(0.0921)
Control		
Population	− 0.3066***	− 0.0485***
	(0.0574)	(0.0107)
Autocommuter	− 0.3153*	− 0.0532*
	(0.1328)	(0.0264)
VMT	0.0587	0.0111*
	(0.0435)	(0.0054)
Income	0.4093***	0.0601***
	(0.0622)	(0.0092)
Age	− 0.1821	− 0.0045
	(0.2276)	(0.0244)
Public_Transport	− 0.0017	0.0008
	(0.0083)	(0.0012)
Bicycle	− 0.0005	− 0.0001
	(0.0016)	(0.0002)
Precipitation	− 0.0065	0.0002
	(0.0073)	(0.0007)
Temperature	0.0396	0.0180*
	(0.0604)	(0.0085)
Interaction		
BSS * Population	− 0.0269***	− 0.0050***
	(0.0073)	(0.0010)
BSS * Income	0.1064*	0.0317***
	(0.0461)	(0.0091)
Year fixed effects	Yes	Yes
Urban area fixed effects	Yes	Yes
Adj. R^2	0.096	0.129
F-statistic	16.176***	19.220***
Observations	960	960

The treatment group dummy (*Treated*) was dropped due to multicollinearity; the natural logarithm was taken for all non-dummy variables. Heteroskedasticity consistent coefficients are reported in parenthesis.
Significant codes: '***' 0.001, '**' 0.01, '*' 0.05.

different areas of cities. More recently, Campbell and Brakewood (2017) found after controlling for the expansion of bike lanes, every thousand bike-sharing docking stations along a bus route is associated with a 1.69% fall in daily unlinked bus trips on roads in Manhattan and Brooklyn of the New York City. This finding serves as a starting point to understand the pathways through which BSSs reduce peak-time congestion and facilitate multimodal transportation, although the interrelation between BSSs and public transport systems need to be further explored and is beyond the scope of this study.

Lastly, a number of studies have pointed out BSSs either directly reduce car usage (DeMaio, 2009; Martin and Shaheen, 2014) or indirectly increase the use of public transport by connecting the last mile (Fishman et al., 2013; Noland and Ishaque, 2006; Shaheen et al., 2013). In a hypothetical back-of-the-envelope scenario, with the launch of BSSs, if a 1% autocommuters switch from automobile to other means of transportation, it will result in an approximately 0.3% reduction in congestion. Indeed, the US National Household Travel Survey (NHTS, 2009) has revealed that 37.6% of trips in private cars and 73.6% of those by bike are < 2 miles, which leaves room for switching from private cars to BSSs.

This work aims to serve as a starting point for researchers, urban policy-makers, and BSS operators to further explore the impact of BSSs. The success and benefits of BSSs depend on the number of trips previously made by car are shifted. They also rely on how (much) users' demand is realized. As for end-users, one of those major perceived benefits of bike-sharing is low-cost and convenience (Fishman et al., 2013). Therefore, policy-makers and BSS managers need to understand BSS users' travel preference (Faghih-Imani and Eluru, 2015; Jimenez et al., 2016) so that locations and the operation of BSS can be optimized (Garcia-Palomares et al., 2012; Lin and Yang, 2011; Médard de Chardon et al., 2016).

Due to data availability issue, there are several limitations of this study, which also casts lights on future research directions. First, this study has only considered the launch of BSSs and its impact on congestion across US cities at a very high level. We were not able to differentiate the effect of the size or coverage of BSSs in each urban area. Further work can focus on how such operation factors of BSSs make a difference. Second, the unit of analysis in this study is at urban area level. Studies at a finer scale (e.g., neighborhood or zip code level) may provide more nuanced knowledge of the impact of BSSs. For example, Zhang et al. (2017) explored how different build environment factors affect the usage of BSSs. Third and relatedly, this work focused on the introduction of BSSs, but not the actual usage. Social factors (e.g., the influence of family, friends, and the workplace) affect users' attitudes to biking in general (Willis et al., 2015). Additionally, Fishman (2016) found a divergence of the socioeconomic profiles of BSS users and those of the general population, where BSSs users are biased to be white males with above average income and education level. Lastly, on the one hand, we appeal for BSS operators to open anonymized operational datasets to the public; on the other hand, we plan to delve into the various factors (e.g., operational, natural environmental, and socioeconomic) of BSSs at multi-level (e.g., facility level, neighborhood level, city level, etc.) on their purported benefits in our future studies.

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