Trying to Solve the Last Mile Gap: Do Docked and Dockless Vehicles Impact Public Transportation Ridership Rates in U.S. Cities?

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March, 2020

Abstract

This project analyzes the potential impact of docked and dockless vehicles on public transportation ridership rates in 126 U.S. cities. As docked and dockless vehicles were introduced in 2015 and 2017 respectively, these novel vehicles offer an opportunity to assess how existing public transportation networks in U.S. cities respond to new modes of transportation. To analyze the potential effect of docked and dockless vehicles on public transportation ridership rates, this paper conducts a staggered entry difference in difference approach using data from 2010-2018. The results of this analysis indicate that there exists a positive effect between the relative size of a pre-existing public transportation network and the introduction of docked vehicles. It also finds that in the average U.S. city, the introduction of a dockless vehicle company leads to a 1.42 million decrease in public transportation ridership rates, although there exists questions surrounding whether this negative effect is caused by the treatment, and thus subsequent analysis needs to be conducted once 2019 ridership data is made available. Lastly, the analysis finds that there is no effect of docked vehicles on public transportation ridership rates in the average U.S. city.

Introduction

In a time where climate action plans are continually being passed in cities and states, there has been an increasing impetus to focus efforts and capital in public transportation as a means of reducing pollution and greenhouse gas (GHGs) emissions. This is largely as the transportation sector is the largest contributor to GHGs as it accounts for 29% of the U.S. total (EPA,2019). However, as cities have invested in their public transportation networks, they have not seen demand increase, as patronage has fallen in many of the top 50 U.S. markets (Mallet, 2018). Excluding New York City (which accounts for 40% of all U.S. transit riders), national ridership has decreased by 7% over the last decade (Mallet, 2018). While this decrease can be attributed to a variety of factors, among them being the introduction of ridesourcing companies such as Lyft and Uber, or decreasing gasoline prices, at the end of the day if cities want to decrease the GHGs in their city, they must work to increase public transportation ridership rates and decrease the use of fossil fuels in the transportation sector.

This paper analyzes the potential effect of docked and dockless vehicles on public transportation ridership rates in networks around the country, to see whether these vehicles have a complementary or substitution effect, or in other words a net positive or negative effect. Although both types of vehicles involve the use of bicycles, docked vehicles are only available at stations from which they are rented out and returned. In contrast, dockless vehicles are bicycles and scooters that can be picked up and left virtually anywhere (although significant recent legislation has limited this ability). In presenting a way to solve the last-mile gap, or the distance from an individual's house or place of work to the nearest node of public transportation, these vehicles have the opportunity to increase the relative ease of using existing transportation networks. However, it is imperative to determine if this desired effect is truly the case, and that individuals are not simply substituting rides that they would have taken on public transportation networks in favor of docked or dockless vehicles. Introduced in 2015 and 2017 respectively, docked and dockless vehicles represent an ideal treatment to see if in fact these developments in the last-mile gap sector have truly had an effect. As docked and dockless vehicles have been introduced in almost all major and minor U.S. cities, this analysis can lay the foundation for further studies in the field, as well as motivate transportation agencies to try to incorporate these new modes into the existing transportation infrastructure.

Literature Review

As docked and dockless vehicles were only recently introduced in the U.S. in 2015 and 2017, I was unable to find a comprehensive academic study that detailed the potential effects of these vehicles on U.S. public transportation rates. As a result, to the best of my knowledge this is the first paper of its kind in which it strives to analyze this relationship. With that being said there does exist literature regarding the impacts of dockless vehicles and Uber on public transportation, and I have largely modeled the statistical analysis of this paper on that literature. Regarding dockless vehicles, there has been a study which analyzed these vehicles impact on public transportation rates in Beijing, China. This study found that there existed a positive complementary effect of dockless vehicles in regards to subway traffic (Jin, 2018). In regards to the study on the potential effects of Uber, the authors found that Uber is a complement for the average transit agency in the U.S., although this result was very heterogenous (Hall, 2018).

Data

To analyze the effect of docked and dockless vehicles on public transportation ridership rates, I had to clean and merge four distinct datasets. These datasets included the following for the 126 cities in the analysis: the year in which docked and dockless vehicles were introduced, the total ridership rates and vehicle miles travelled of public transportation, the annual gas price, and the annual amount of precipitation.

The dataset containing information on the year in which docked and dockless vehicles appeared in a given city was obtained via the Assistant Secretary for Research & Technology in the Bureau of Transportation Statistics in the National Transportation Atlas Database. As the dataset contained a multitude of observations from 2015-2019, I had to clean the dataset so that only my variables of interest remained, which were state, city, scooter count, dockless count, and docked count. As these variables are the policy variables of interest, it is important to specify how they are measured. In terms of the docked count, this variable is measured by the number of docking stations. In contrast, both the dockless count and the scooter count are measured by how many companies are present in the city. Because of the limited scope of the dataset, at cause of how new the presence of dockless vehicles and scooters are, I also created a new variable to represent the sum of dockless and scooter companies in each city, which designated as dockless, will represent the policy variable of interest in regards to dockless vehicles. It is also important to note that both of these policy variables analyze the relative intensity of treatment, as well as acting as variables which demonstrate if docked or dockless vehicles exist.

After cleaning and manipulating the data on docked and dockless vehicles, I then obtained a dataset of total ridership and vehicle miles traveled from the Department of Transportation (DOT), which in the analysis will function as dependent variables. As this analysis employs a staggered entry difference in difference approach, data is used from 2010-2019. To create the dataset which contained the total vehicle miles and total ridership rates, I exported the variables representing year, city, state and both total ridership and vehicle miles traveled per year from each yearly DOT annual database. As the DOT did not agglomerate total ridership and total vehicle miles traveled by city until after 2014, I had to pick through the data to analyze which transit agency belonged to which city. Furthermore, it is worth mentioning that after further analysis, the 2019 dataset was not used as after reviewing the data, the totals for both total vehicle miles traveled and ridership were identical for most transit agencies to the 2018 data. It is also important to note that because of the nature of ridership, this variable is measured in units of thousands.

Using aspects of the statistical design of the aforementioned literature (Jin, 2018), the analysis also employs the use of control variables regarding the annual gas price as well as the annual precipitation level in each city. The data surrounding annual gas prices per city was obtained from the U.S. Energy Information Administration. As this dataset recorded the average price of all conventional grades of gas at the beginning of every week, I had to create the average price per year using the AVERAGE function in Excel. Furthermore, as this dataset did not have specific information on all cities in the analysis, I had to pick the best option to represent the gas price in each respective city. This means that some of the 126 cities have gas prices that represent the annual gas price of their state, and some the annual gas price of their region when state available was not available.

In regards to the control variable for precipitation, I created this dataset by employing remote sensing techniques using Google Earth Engine Coder, to create a table depicting the annual precipitation rates for each respective city in my study. I went about this by uploading the shapefile of the 126 cities into Google Earth Engine Coder and subsequently selected the NASA Daily Surface Weather and Climatological summaries (DAYMET) sum of precipitation by calendar year. I then created a 5km buffer around each city and ran the ReduceRegions function. This function allowed me to generate the sum of all precipitation which occurred in each respective city in a specific year. I did this same process for the years 2010-2018 and agglomerated this data to make my precipitation dataset.

After obtaining all four of these datasets, and properly cleaning and manipulating them, I then proceeded to merge them into a master dataset using STATA.

Methodology

Although both docked and dockless vehicles use bicycles and have the same general functions of solving the last mile gap, they represent two different treatments. Docked vehicles require a user to leave them at a dock station, while dockless vehicles can be left anywhere. As they differ in their treatments but aim to have the same desired effect, both of these treatments are used in the estimating equation and subsequent regressions. Additionally, because docked and dockless vehicles were introduced in 2015 and 2017 respectively, it would be naïve to think that users of docked vehicles would not be enticed to switch to dockless vehicles because of the added convenience of being able to leave the bikes anywhere, in other words meaning that it would be misconstrued to run the regression on only one treatment. However it is important to note, that because this analysis is conducted using a staggered entry approach, to properly measure the relative impact of leads and lags, regressions on one treatment are also run in the analysis.

As the analysis is conducted on a dataset containing information about 126 cities, it is imperative to test for parallel trends to analyze if in fact there exists issues of endogeneity in the timing of entry or intensity of entry of both docked and dockless vehicles. As seen in Figure 1(Appendix) and Figure 2 (Appendix), while there is no clear violation of parallel trends in the entry date of both treatments, there exists a violation of parallel trends in the relative intensity of treatment in certain cities in the dataset. As the violation of parallel trends exists, the analysis contains unit-specific trends to account for this potential bias. Additionally, because this analysis is one of staggered entry leads and lags of each treatment are included in the main estimating equation. As so, the main estimating equation for the analysis is the following:

$$y_{it} = \alpha_{0i} + \alpha_{1i}t + \lambda_t + \delta_1 T_{it} + \delta_2 T_{it-1} + \delta_3 T_{it+1} + \delta_4 T_{it+2} + \delta_5 U_{it} + \delta_6 U_{it+1} + \beta_3 X_{it} + \beta_4 Y_{it} + \epsilon_{it}$$

Where y_{it}= total ridership per city α_{0i} = City wide fixed effects, $\alpha_{1i}t$ = City-specific time trends, λ_t= Year fixed effects, T_{it}= the treatment effect if there are docked vehicles, T_{it+1} = the treatment effect if there are docked vehicles with a one year lead, T_{it+2} = the treatment effect if there are docked vehicles with a two year lead , T_{it-1} = the treatment effect if there are docked vehicles with a one year lag, U_{it}= the treatment effect if there are dockless vehicles, U_{it+1} = the treatment effect if there are dockless vehicles with a one year lead, X_{it}=The effect of the control of gas prices, Y_{it}=The effect of the control of annual precipitation, and ϵ_{it}=the associated error term.

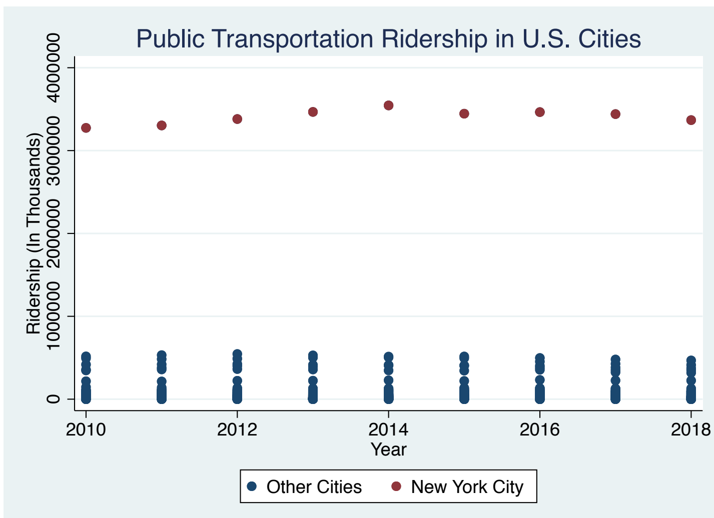
Results

This analysis comes up with two main conclusions, that in cities which have solid pre-existing transportation infrastructure there is a positive complementary effect of docked vehicles, and that there exists a negative substitution effect of dockless vehicles on public transportation ridership rates, although this result has issues in terms of the presence of statistically significant leads. Lastly it is important to note that docked vehicles did not appear to have an effect on the public transportation ridership rates in the average U.S. city.

Because of the relative setup of the U.S. transportation industry, in which New York City is responsible for about 40% of all U.S. transit riders (Mallet, 2018), before conducting the analysis the relative ridership rates of all 126 cities in the dataset were analyzed as a means to test for the potential impact of the city itself. As seen in Figure 3, the ridership rates of New

York City in regards to the other cities in the dataset are astounding. As trying to make conclusions based off of a regression which included New York City could be misleading, this paper takes the approach of presenting the main findings after omitting the city. That is not however to say that a regression with New York city was not run, as this can be seen in Tables 2-3 (Appendix), demonstrating that the city augmented the relative effects of both treatments because of its high concentration of public transportation trips.

Figure 3



Once excluding the city of New York, the regression surrounding the effects of dockless and docked vehicles becomes more representative of the rest of the cities in the dataset. In Table 1 there are two notable conclusions to draw, the first being that docked vehicles are positively correlated to having an effect in cities where more people use public transportation networks, and the second, that dockless vehicles appear to have a substitution effect in U.S. cities, although it is important to note that the dockless vehicles lead is highly significant. The first conclusion, that docked vehicles are positively correlated with better transportation networks, is supported by regression 1, which states that without distinguishing the differences between cities, on average every docked station increases public transportation ridership by 821,600 trips. However, it is important to note that this regression does not include city fixed effects or city time trends indicating that it can only conclude that with increasing overall ridership in U.S. cities docked vehicles appear to have a complementary effect.

The second conclusion, relating to the substitution effect of dockless vehicles in U.S. cities, can be seen in regression 3 of Table 1. This regression demonstrates that for each additional dockless company that comes to operate within a city, there is a decrease in ridership by a magnitude of 1.42 million trips. It is important to note however, that the dockless lead is highly significant, although the effect of the dockless treatment remains negative and statistically significant. This does however raise questions about the certainty and the magnitude of the result as there appears to be a trend of decreasing ridership before dockless vehicles were introduced.

It is also important to note how although docked vehicles are positively correlated to having an effect in cities where more people use public transportation networks, once incorporating city time trends and city fixed effects, the effect of docked vehicles is statistically insignificant.

Table 1: Summary Regression Table

	(1) Ridership	(2) Ridership	(3) Ridership
Docked Vehicles	821.6***	-47.03***	-6.140
	(45.385)	(5.399)	(6.081)
Dockless Vehicles	-3592.0	-1512.7***	-1417.8***
	(3002.544)	(197.963)	(335.701)
Gas Price	94884.0***	5261.4*	3953.5
	(11989.140)	(2534.772)	(2645.854)
Rain	0.000117*	-0.00000525	0.000000789
	(0.000)	(0.000)	(0.000)
Docked Vehicles Lead			-11.89
			(6.154)
Docked Vehicles Lag			-47.68***
			(6.257)
Dockless Vehicles Lead			-741.4***
			(216.064)
2 Year Docked Vehicles Lead			
Constant	-277596.1***	-1960656.1*	-944753.7
	(39120.417)	(927939.576)	(1111773.002)
N	1124	1124	876
adj. R^2	0.276	0.601	0.619

Standard errors in parentheses. The observations for New York City were dropped before any regression was ran. Regression 1 uses the fixed effects estimator without including a unit dummy. Regression 2-3 uses the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects. Regression 3 includes both 1 year leads for docked and dockless and a 1 year lag for docked.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robustness Checks

As specified by Figure 1, the relative ridership rates in New York were much higher than those in the other cities in the dataset, and as a result this observation was dropped. However as seen in Figure 4 (Appendix), this heterogeneity was not only seen in the case of New York City, as there is a clear distinguishable divide between the relative ridership rates of major U.S. metropolitan areas and the other cities in the dataset. As this heterogeneity based on city size is evident throughout the dataset, this analysis employed the use of three sample sizes to analyze the previous stated results. As seen in Tables 2-7 (Appendix), this analysis employed regressions using all the cities that comprised the dataset, using all cities excluding New York, and lastly a regression of all cities excluding cities which comprise the major public transportation networks given in Figure 4 (Appendix). These tables repeat the general regressions displayed in Table 1 as well as include additional regressions, among them treatment specific leads and lags. It is worthy to note that although there is a change in the magnitudes of both the positive complementary effect of docked vehicles in cities which have solid pre-existing transportation infrastructure, and the negative substitution effect of dockless vehicles on public transportation ridership rates, in each of the three regression models the overall outcome of the effects is the same. The exception to this is an apparent negative substitution effect demonstrated in regression 1 of Table 2 (Appendix), but this can be largely attributed to the presence of New York City as once the city is removed from the data this finding no longer exists. Because the analysis yields the same general effects are running the regression on different sample sizes, this proves that the findings made in Table 1 are robust to different sample sizes.

The second robustness check of the analysis came in running regressions 2 & 3 specified in Table 1 with weights, representing the average ridership rates travelled per city between the period of 2010-2018. As seen in Table 8 (Appendix) these regressions gave similar results to the effects of changing the sampling size, demonstrating a negative substitution effect of dockless vehicles public transportation ridership rates, although the magnitude once again changed. It is important to note that although the dockless lead expressed in regression 3 of Table 8 is statistically significant and larger than the coefficient on the treatment, as seen in regression 5, once running a regression with only the dockless treatment, the coefficient on the treatment is once again larger. While this does raise some concerns with the magnitude and effect of the treatment overall, it follows the effects seen in Table 1.

The final robustness check consisted of creating coefficient plots for both the docked and dockless treatments, to analyze if either treatment had a notable impact on public transportation ridership rates and that they did not simply follow a pre-noticeable trend. In analyzing Figure 5 (Appendix), there appears to be no issues pertaining to ashenfelter's dip in regards to the effect of docked vehicles on public transportation ridership rates. However, because of the statistically insignificant nature of docked vehicles on public transportation ridership rates, it can be concluded that this figure may pick up on other changes in the transportation sector. In regards to the negative substitution effect of dockless vehicles, as seen in Figure 6 (Appendix), there appears to be a slight ashenfelter's dip, which raises questions about the strength of the effect of dockless vehicles on public transportation rates. Additionally it is important to note that none of the confidence intervals appear to be statistically significant, raising further questions about the ability of this figure to conclude anything. Lastly, it must be said that as there is only one year of analysis post treatment, to make a definite conclusion regarding the potential impact of an ashenfelter's dip there is a need for further data.

Econometric Challenges

Although the analysis was made to be as thorough as possible, there exists a plethora of shortcomings specifically in regards to how the data was collected and assembled and the underlying assumptions used to make the conclusions of the analysis. To being with the, the greatest econometric challenge is being able to account for the huge impact of ridesourcing services on public transportation ridership rates. Although the literature says that Uber has a complementary effect on public transportation(Hall, 2018), the authors do conclude that there is considerable heterogeneity in their results. As Uber could largely have led to a decrease in public transportation rates across the cities in the dataset, this effect could overshadow the effects of both docked and dockless vehicles affecting the analysis of this paper.

A second major concern, is that in only being able to compare public transportation ridership rates to the number of docked stations and companies which operate dockless vehicles, the analysis makes the generalized claim that the mere presence of these identifiers will effect public transportation rates. This analysis would be significantly more robust if the dataset on docked and dockless vehicles included the total miles traveled on each respective mode of transportation. This could then account for the fact that there may be different ridership tendencies across cities surrounding the uptake of docked and dockless vehicles potentially attributable to geographical, cultural, political or age factors.

Another challenge of the analysis comes from the relative limitations of the data that was assembled. To begin with, there is a large issue with the fact that the DOT does not have updated information on total vehicle miles travelled or total ridership by transit agency for 2019. While the dataset on docked and dockless vehicles has information from 2015-2019, the majority of its data on scooter counts comes in 2018-2019, with only Santa Monica appearing to have these devices in 2017. Additional issues with the analysis could stem from the fact that there was not readily available information in regards to the gas prices in each respective city. Because this data was agglomerated by state and region when a city price was not able to be found, this can affect the certainty of the analysis.

Conclusion

This project analyzes the potential impact of docked and dockless vehicles on public transportation ridership rates in 126 U.S. cities. Using a difference in differences approach this analysis finds that there exists a positive complementary effect between the relative size of the pre-existing public transportation network and the introduction of docked vehicles. It also finds that in the average U.S. city, the introduction of a dockless vehicle company leads to a 1.42 million decrease in public transportation ridership rates, although there exist questions surrounding whether this negative substitution effect is caused by the effect of the treatment, and not simply a trend that was already existing. To answer this question more analysis needs to be conducted once data from 2019 is more readily made available. This paper also finds that there is no effect of docked vehicles on the public transportation rates in the average U.S. city. This analysis can be seen as motivation for cities and public transportation agencies to come up with policies and solutions to see how they can potentially incorporate dockless vehicles into existing public transportation networks. Through the process of reversing the negative substitution effect of dockless vehicles in regards to public transportation ridership rates, city agencies can take advantage of this new mode of solving the last mile gap, in the process reducing GHG emissions. Additionally, the conclusion of there is a positive complementary relationship between docked vehicles and public transportation rates supports the argument of building more fixed transportation infrastructure. Cities and transit agencies should take this seriously, as with evidence supporting the argument of increasing returns to scale in regards to public transportation networks, cities should continue to heavily invest in the sector, in the process bolstering their ability to ultimately combat GHG emissions.

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Appendix

Figure 4

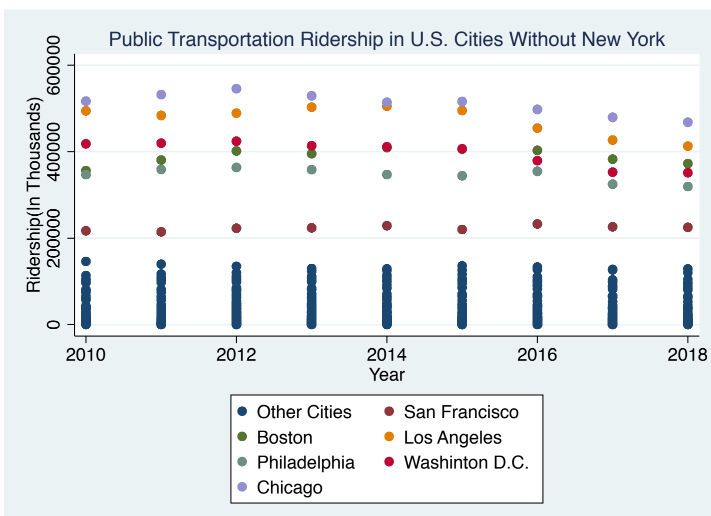

Figure 1: Evaluating Parallel Trends for Docked Vehicles

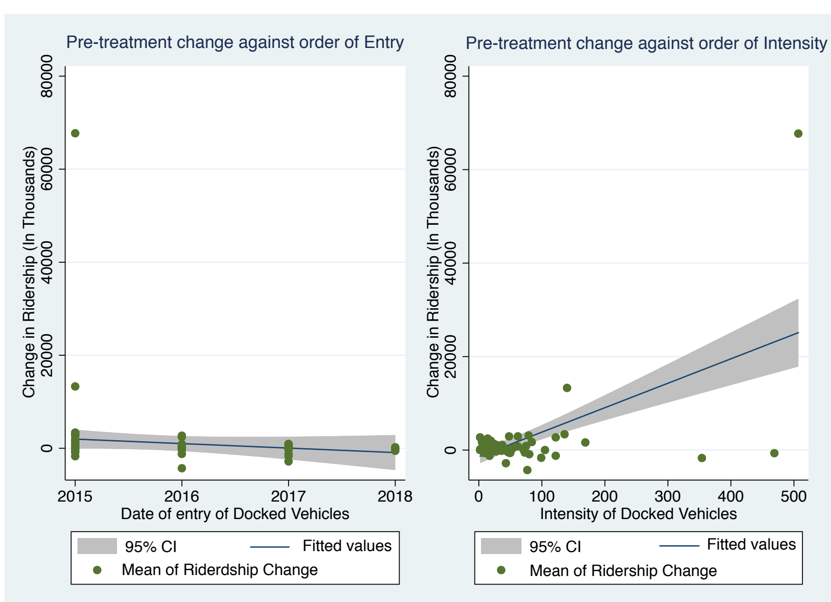

Figure 2: Evaluating Parallel Trends for Dockless Vehicles

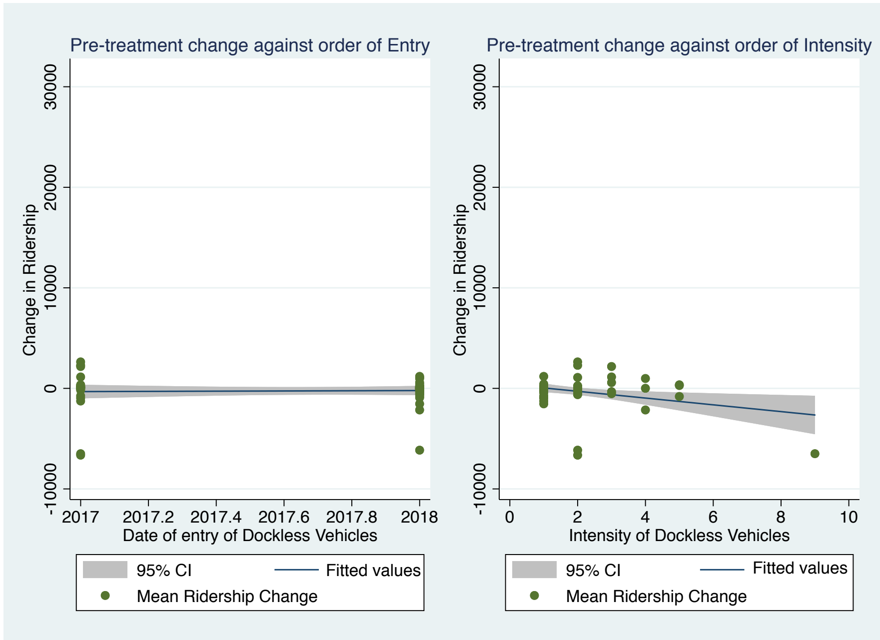

Figure 5

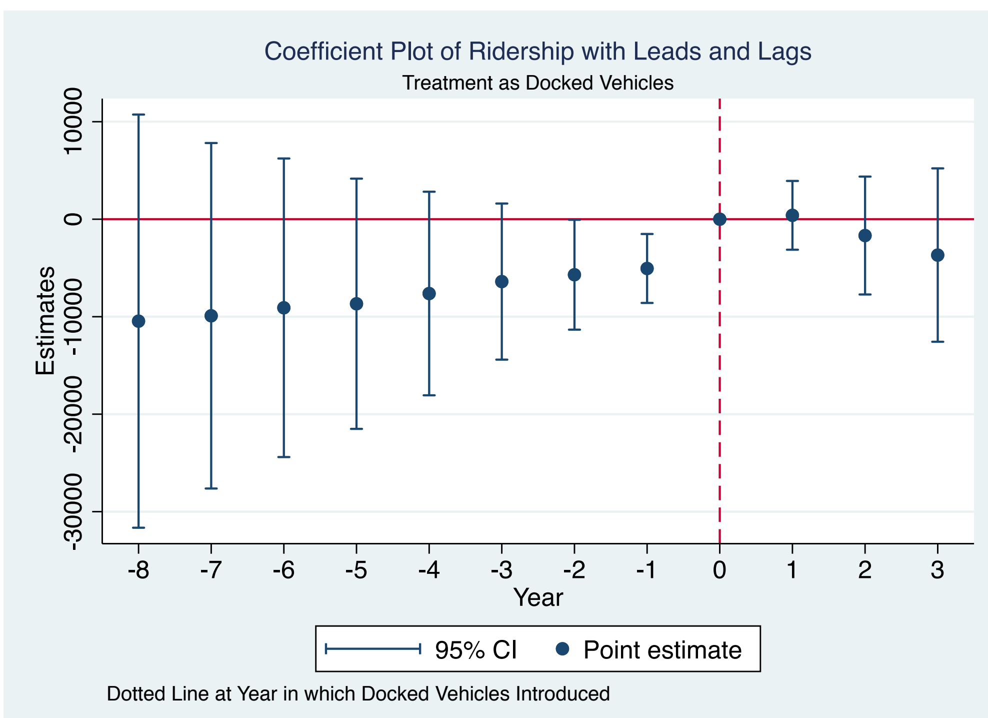

Figure 6

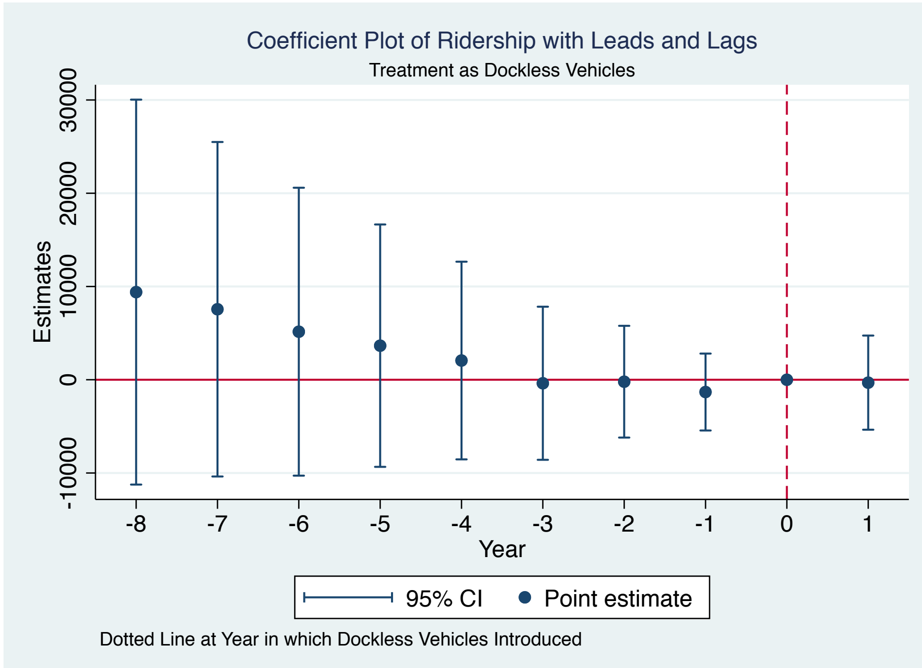

Table 2: General Regressions

	(1) Ridership	(2) Ridership	(3) Ridership	(4) Ridership
Docked Vehicles	2478.8***	-18.70***	-17.73**	-149.6***
	(125.996)	(5.667)	(5.600)	(8.947)
Dockless Vehicles	-42044.9***	-2042.3***	-2090.9***	-796.8*
	(10631.949)	(404.236)	(359.340)	(394.851)
Gas Price	129309.4**	-551.2	587.1	2553.2
	(43586.931)	(4142.331)	(562.706)	(5052.305)
Rain	0.000341	-0.0000190	-0.0000177	-0.0000162
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-403974.5**	65889.1***	64178.0***	-3525306.6
	(142214.186)	(12202.357)	(2381.911)	(1854525.565)
N	1133	1133	1133	1133
adj. R^2	0.257	-0.049	-0.053	0.420

Standard errors in parentheses. Regression 1 uses the fixed effects estimator without including a unit dummy. Regression 2 uses the fixed effects estimator by identifying by city and subsequently running time fixed effects. Regression 3 uses the fixed effects estimator by identifying by city and running city fixed effects. Regression 4 uses the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: General Regression Leads and Lags

	(1) Ridership	(2) Ridership	(3) Ridership
Docked Vehicles	-147.8***	-151.5***	
	(8.936)	(8.982)	
Dockless Vehicles	-2046.7***		-2609.6***
	(599.169)		(691.771)
Gas Price	1657.6	3249.7	12429.8*
	(5219.971)	(5075.465)	(5491.447)
Rain	-0.00000722	0.00000219	0.000000922
	(0.000)	(0.000)	(0.000)
Docked Vehicles Lead	527.1	-541.9	
	(1036.106)	(1157.963)	
Docked Vehicles Lag	-761.9	-720.4	
	(1444.479)	(1637.067)	
Dockless Vehicles Lead	237.2		213.1
	(1182.294)		(1364.494)
2 Year Docked Vehicles Lead		-1348.5	
		(927.690)	
Constant	-2628898.7	-3866543.0	-2441644.6
	(2248912.351)	(2610515.666)	(2182068.207)
N	883	758	1008
adj. R^2	0.472	0.531	0.403

Standard errors in parentheses. Regression 1-3 use the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects. Regression 1 includes both 1 year leads for docked and dockless and a 1 year lag for docked. Regression 2 limits the analysis to just docked vehicles, including both 1 and 2 year leads and lags. Regression 3 limits the analysis to just dockless vehicles, including solely a 1 year lead.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: General Regressions Excluding New York

	(1) Ridership	(2) Ridership	(3) Ridership	(4) Ridership
Docked Vehicles	821.6***	-58.32***	-57.16***	-47.03***
	(45.385)	(3.785)	(3.744)	(5.399)
Dockless Vehicles	-3592.0	-1451.6***	-1396.0***	-1512.7***
	(3002.544)	(212.965)	(190.694)	(197.963)
Gas Price	94884.0***	933.4	-15.97	5261.4*
	(11989.140)	(2138.851)	(293.469)	(2534.772)
Rain	0.000117*	-0.00000528	-0.00000444	-0.00000525
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-277596.1***	34473.2***	38180.8***	-1960656.1*
	(39120.417)	(6303.531)	(1241.490)	(927939.576)
N	1124	1124	1124	1124
adj. R^2	0.276	0.235	0.229	0.601

Standard errors in parentheses. The observations for New York City were dropped before any regression was ran. Regression 1 uses the fixed effects estimator without including a unit dummy. Regression 2 uses the fixed effects estimator by identifying by city and subsequently running time fixed effects. Regression 3 uses the fixed effects estimator by identifying by city and running city fixed effects. Regression 4 uses the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: General Regressions Excluding New York Leads and Lags

	(1) Ridership	(2) Ridership	(3) Ridership
Docked Vehicles	-6.140	-30.84^{***}	
	(6.081)	(6.713)	
Dockless Vehicles	-1417.8^{***}		-1830.8^{***}
	(335.701)		(381.550)
Gas Price	3953.5	1810.8	7394.2^{**}
	(2645.854)	(2520.405)	(2684.104)
Rain	0.000000789	0.00000538	0.00000122
	(0.000)	(0.000)	(0.000)
Docked Vehicles Lead	-11.89	-8.713	
	(6.154)	(5.927)	
Docked Vehicles Lag	-47.68^{***}	-36.34^{***}	
	(6.257)	(6.700)	
Dockless Vehicles Lead	-741.4^{***}		-1322.4^{***}
	(216.064)		(230.125)
2 Year Docked Vehicles Lead		-31.85^{***}	
		(6.704)	
Constant	-944753.7	-1796377.0	-1582237.7
	(1111773.002)	(1279547.068)	(1052990.617)
N	876	752	1000
adj. R^2	0.619	0.428	0.489

Standard errors in parentheses. The observations for New York City were dropped before any regression was ran. Regression 1-3 use the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects. Regression 1 includes both 1 year leads for docked and dockless and a 1 year lag for docked. Regression 2 limits the analysis to just docked vehicles, including both 1 and 2 year leads and lags. Regression 3 limits the analysis to just dockless vehicles, including solely a 1 year lead.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: General Regressions Excluding Major Metropolitan Areas

	(1) Ridership	(2) Ridership	(3) Ridership	(4) Ridership
Docked Vehicles	393.0***	-8.341	-9.627*	-12.09*
	(35.234)	(4.507)	(4.346)	(5.411)
Dockless Vehicles	3988.3**	-930.8***	-986.0***	-1034.3***
	(1278.434)	(140.184)	(124.270)	(120.720)
Gas Price	16566.2***	2294.9	567.5**	2547.5
	(4515.816)	(1259.824)	(173.656)	(1365.914)
Rain	0.00000170	0.00000316	0.00000128	0.00000203
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-36168.3*	11791.0**	17077.2***	-1605685.0***
	(14669.333)	(3699.867)	(725.846)	(479310.968)
N	1070	1070	1070	1070
adj. R^2	0.129	-0.003	-0.009	0.563

Standard errors in parentheses. The observations for the major metropolitan areas of San Francisco, Chicago, Los Angeles, Philadelphia, Washington, Boston and New York were dropped before the analysis. Regression 1 uses the fixed effects estimator without including a unit dummy. Regression 2 uses the fixed effects estimator by identifying by city and subsequently running time fixed effects. Regression 3 uses the fixed effects estimator by identifying by city and running city fixed effects. Regression 4 uses the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: General Regressions Excluding Major Metropolitan Areas Leads and Lags

	(1)	(2)	(3)
	Ridership	Ridership	Ridership
Docked Vehicles	-8.927	-9.947	
	(5.997)	(7.185)	
Dockless Vehicles	-1198.3***		-1496.3***
	(233.694)		(240.200)
Gas Price	3418.9*	2289.0	2386.5
	(1543.005)	(1639.374)	(1451.313)
Rain	0.00000631*	0.00000698	0.00000604*
	(0.000)	(0.000)	(0.000)
Docked Vehicles Lead	500.8	761.3*	
	(295.465)	(361.808)	
Docked Vehicles Lag	-932.3*	-351.7	
	(419.064)	(518.338)	
Dockless Vehicles Lead	-713.6*		-970.6**
	(338.249)		(350.848)
2 Year Docked Vehicles Lead		596.6*	
		(295.156)	
Constant	-641098.3	-473379.9	-1327055.0*
	(624825.018)	(797454.457)	(545347.414)
N	834	716	952
adj. R^2	0.557	0.462	0.513

Standard errors in parentheses. The observations for the major metropolitan areas of San Francisco, Chicago, Los Angeles, Philadelphia, Washington, Boston and New York were dropped before the analysis. Regression 1-3 use the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects. Regression 1 includes both 1 year leads for docked and dockless and a 1 year lag for docked. Regression 2 limits the analysis to just docked vehicles, including both 1 and 2 year leads and lags. Regression 3 limits the analysis to just dockless vehicles, including solely a 1 year lead.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Weighted Regressions with Leads and Lags

	(1) Ridership	(2) Ridership	(3) Ridership	(4) Ridership
Docked Vehicles	-32.37***	7.917	-30.98***	
	(5.728)	(6.504)	(7.183)	
Dockless Vehicles	-965.2***	-1113.6**		-1475.2***
	(272.059)	(393.837)		(425.103)
Gas Price	22093.4***	14211.9*	2446.1	35775.4***
	(5316.756)	(5554.300)	(5459.754)	(5312.755)
Rain	-0.0000521***	-0.0000619***	-0.0000197	-0.0000354*
	(0.000)	(0.000)	(0.000)	(0.000)
Docked Vehicles Lead		-22.84***	-24.56***	
		(6.684)	(6.266)	
Docked Vehicles Lag		-32.47***	-31.07***	
		(6.348)	(6.837)	
Dockless Vehicles Lead		-1478.1***		-1276.3***
		(316.414)		(317.464)
2 Year Docked Vehicles Lead			-48.48***	
			(7.710)	
Constant	75410.6	966987.0	-7646147.8*	-624180.5
	(1862171.612)	(2442331.833)	(2999835.027)	(2102114.362)
N	1124	876	752	1000
adj. R^2	0.741	0.717	0.497	0.652

Standard errors in parentheses. Regressions 1-4 use the fixed effects estimator by identifying by city and running city fixed effects, time fixed effects as well as unit-specific fixed effects. Regressions 1-4 are ran using the average ridership in each respective city from 2010-2018 as the weight. Regressions 2 includes both 1 year leads for docked and dockless and a 1 year lag for docked. Regression 3 limits the analysis to just docked vehicles, including both 1 and 2 year leads and lags. Regression 4 limits the analysis to just dockless vehicles, including solely a 1 year lead

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$