Assessing the Benefits of Micromobility

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Abstract

Advancements to battery technology have had spillover effects on many new modes of transportation in urban travel that extend beyond electric vehicles. In this paper, I examine the emission and congestion benefits attributable to fewer gasoline vehicle use due to the substitution to micromobility electric scooters. A discrete choice, random utility framework is employed to estimate existing mode demand and then the mode demand of electrified scooters. I focus on the importance of local factors in assessing pollution and congestion damages and the benefits from scooter adoption. I find that the full adoption of electrified scooters in the major 52 U.S. cities can create a positive externality of $2.75 million in environmental benefits and $6.01 billion in congestion benefits annually and I document the local heterogeneity in benefits across 52 cities. This paper shows that highly dense urban cities with high marginal congestion, large damages from emissions and a clean electric grid, such as Los Angeles, California, imply greater environmental and congestion benefits from switching to electric scooters as compared to less dense, less congested cities, with lower emission damages, and a less clean electric grid that draws on power from coal powered plants such as Memphis, Tennessee.

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1 Introduction

Improvements to battery technology used in electric vehicles over the last two decades have extended the power, range and speed of electric vehicles whilst reducing the production cost of efficient, energy dense batteries. These advancements in electric vehicles have spurred spillover effects on many other modes of transportation, in particular on micromobility devices such as electric scooters and electric bikes. Traditional scooters and bikes have been redesigned with electric batteries extending their speed and range, while reducing rider effort. As a result of this product advancement, newly designed electric scooters have now become popular modes of short distance transportation in many metropolitan areas.

Several private rental operators of electric scooters have sprung up in recent years in over 129 cities offering their service of short term rentals of e-scooters and have seen tremendous ridership growth since their inception. As of the end of 2018, over 85,000 e-scooters were available for public use in about 100 U.S. cities seeing an estimated 38.5 million trips and as of 2019, e-scooter rides surpassed traditional bike rides on bike sharing programs.[1] Ride share operators such as Bird and Lime rent out scooters by the minute, and riders leave them at their final destination to be claimed by the next user. This dockless model of rentals is appealing to many urban customers as the fleet of scooters are not centrally stationed for pick-up and drop-off but rather scattered throughout a city making them more accessible.

Due to this new growing popularity in micromobolity, e-scooters have the potential to displace many short distance vehicle rides in some major cities. In a Lime survey of 600 user respondents in San Francisco, 61.8% reported that had they not taken an e-scooter on their most recent trip that their second best alternative would have been either an Uber/Lyft/Taxi or a personal vehicle ride. In a separate Lime survey on Los Angeles users, two in five respondents reported to using Lime to replace travel by car. Another survey ranking consumers mode choices done by Portland Oregon's Public Bureau of Transportation, showed that 34 percent of participating Portland residents said

[1] In 2018, of the 84 million micromobility trips taken, 38.5 million of those were on scooters. The other 45.5 million trips were on bikes — either ones from station-based bike-shares or dockless shared bikes.

they would have taken a personal car or used a ride-hailing service or taxi had scooters been unavailable; that percentage was even higher among visitors and travelers to the city.

When consumers choose to take a vehicle ride for a trip, they create both a negative environmental and congestion externality that they ignore when making their own mode choice of travel but which others in their locale incur. As a result, when urban consumers substitute their short distance vehicle rides with e-scooters their decision creates a positive gain of less car pollution being emitted and less traffic congestion on the roads. Traffic congestion cost, the time lost idle in traffic, alone costs each American car rider 97 hours or $1,348 a year. Nationally 60% of car trips are short distance trips less than 5 miles, which is well within the maximum feasible range of a trip by an e-scooter on a full charge. Therefore micromobility has the potential to displace many short distance trips and in the long-run reduce the number of personal, ride sharing, taxi and rental vehicles on the road. This would relieve traffic congestion and reduce total vehicle emissions.

In this paper, I analyze the environmental and congestion benefits of electric scooter trip, accounting for the forgone mode of gasoline vehicle use. In particular, I focus on the importance of local factors in assessing pollution and congestion and the geographic heterogeneity of damages. In my analysis, I find that electric scooters create a positive externality of $2.75 million in environmental benefits and $6.01 billion in congestion benefits annually and furthermore I document the local heterogeneity in benefits across 52 cities. I find that highly dense urban cities with high congestion, large damages from emissions and a clean electric grid, such as Los Angeles, California, capture lots of environmental and congestion benefits from switching to electric scooters as compared to less dense, less congested cities, with lower emission damages, and a less clean electric grid that draws on power from coal powered plants such as Memphis, Tennessee.

The first step in determining the environmental and congestion benefits of scooters is to quantify the potential adoption of e-scooters as a mode of everyday travel. Using a trip level, survey dataset from the National Household Transportation Survey (NHTS), I estimate a discrete choice model of mode choice on the existing choices of travel of walking, biking, vehicle, and metro transportation. The survey, conducted by the Federal Highway Administration, documents the trips of 500k trips from 91k households across the United States in 52 metropolitan cities and rural areas. From the estimated model, I calculate the consumers mode demand and the heterogeneous value of travel time of different consumers. I then introduce electric scooters to the choice set of traveling consumers and re-estimate consumers mode demand. Calculating the mode demand for electric scooters and the attributable reduction in vehicle demand, I am then able to assess the environmental and congestion benefits as a result of the introduction of electric scooters. To calculate environmental benefit I use the results of an integrated assessment model that connects emissions from local sources into damages. I map vehicle share reduction and the vehicle miles substituted into marginal damages of emission net of the of emission damages as a result of the charging needs of the electric scooters. For congestion benefit, I empirically derive the congestion function for each city as a function of its number of vehicle drivers. By doing so I account for the heterogeneity in the impact of vehicle reduction on the annual congestion of each city. I use a first order approximation to estimate the marginal congestion for each city. I then map the vehicle share reduction attributable to the introduction of electric scooters into annual congestion time savings. Since improvements in congestion impact the time cost characteristics of vehicle driving that influence mode shares, I conduct a total impact estimation to account for endogeneity when calculating congestion benefit.

Previous Literature

While the literature on micromobility as a research area is sparse, a few research papers have attempted to analyze both the internal and external benefits of bike sharing programs and e-scooters. Faghih-Imani, et al. (2017) examined the hypothesis that bicycles can compete with cars in terms of travel time in NYC and found that during weekdays for more than half of trips less than 3 km, bike sharing was either faster or just as fast as taxi cab travel. Zhang, Mi (2016) estimated the impacts of bike sharing on energy use and CO_2 and NO_x emissions in Shanghai and they found it saved 8,358 tonnes of gasoline fuel and decreased CO_2 and NO_x emissions by 25,240 and 64 tonnes, respectively. Specifically to e-scooters, Hollingsworth et al. (2018) conducted a life-cycle analysis of the environmental impact of e-scooters assessing the external costs associated with the manufacturing, materials, and transportation of creating an e-scooter. Their research however does not model the mode choice reduction in gasoline vehicle market share lost to e-scooters. Unlike these prior papers in the literature, my research takes an empirical demand approach to model the potential market share of electric scooters as a mode choice of everyday travel and assess the heterogeneity in costs and benefits associated with that share.

My methodology follows a long line of discrete choice research papers on traveling and commuting within the transportation literature. Ben-Akiva and Lerman (1975) applied a multinomial logit methodology to the choice between a number of different alternatives for the journey to work in Washington. Wardman, et al. (2006), employed a multinomial logit model to UK commuters mode choice with a special emphasis on their propensity to cycle to work and extend their mode choice model to forecast trends in urban commuting shares and to predict the impacts of different government policy measures to encourage cycling. Aside from modal choice, the multinomial logit methodology has also been extensively applied to other transport decisions such as the number of cars to own (Alperovich et al., 1999; Bhat and Pulugurtha, 1998 and Cragg and Uhler, 1970); choice of car type (Lave and Train, 1979 and McCarthy, 1996); tourist destination (Eymann and Ronning, 1997) and choice of departure time (McCafferty and Hall, 1982). In addition to commuting, a number of studies have analysed mode choice for other journey purposes, using a variety of methods for trips to visit friends and relatives, Domencich and McFadden (1975) for shopping trips, Ewing et al. (2004) for mode choice for the journey to school and McGillivray (1972) for other journey purposes including personal business, visiting friends and relations, shopping and other recreation.

This paper also follows a a recent line of research assessing the benefits of electrification. Hsieh et al. (2018) used a system dynamics approach to examine the air pollution mitigation potential of transitioning gasoline seated scooters to electric seated scooters in Taiwan and found emission factor reduction associated with the switch. Sheng et al. (2016) compared electric motorcycles to gasoline-powered motorcycles on urban noise, finding that electrification can reduce noise pollution. Holland et al. (2016) employed a discrete-choice model of vehicle purchases and conducted an econometric analysis of electricity emissions and found that the environmental externalities from driving electric vehicles depends critically on damages from local pollution. One differentiating contribution this research on assessing the benefits of electric scooters adds to the electrification literature is that the analysis includes the addition of a brand new transportation mode technology that can impact the demand of any of the existing modes rather than a purely gasoline-to-electric substitution within a specific mode. This has not only an enviromental implications but congestion implications as well.

This is the first study to fully empirically and comprehensively model the environmental and congestion benefits of e-scooters as a micromobility asset with a consumer demand model and, as Holland et al. have conducted for electric vehicles, first to consider the geographic variation in damages from local pollutants emitted by both gasoline and e-scooters and to model this variation by means of a discrete choice model. My first set of results documents the adoption rate of e-scooters as a mode choice for 52 major cities. I do so by laying out and estimating several likely standard logit discrete choice models and then estimating the adoption rate. My second set of results documents the considerable heterogeneity in the environmental benefits as well as congestion benefits of a e-scooters as well an estimate for the value of travel time by consumers.

The outline of this paper is as follows: In Section 2, I describe the various data sources I use for estimation. In section 3, I layout the random utility model for transportation mode choice. In section 4, I discuss estimation and identification strategy for estimating the model. And in section 5 I discuss my estimated models, findings and results.

2 Data

The analysis of this paper is based on several main datasets spanning both revealed preference and stated preference of trip choice.

National Household Transportation Survey

The main dataset used to estimate the discrete choice model on mode of travel is the National Household Transportation Survey (NHTS) which is a trip level dataset on the transportation behavior of 91,000 households in the United States. The survey tracks individual and trip level information of households such as the mode of transportation used, the staring time, ending time and distance of each trip and collects individual information about the individual. For the purposes of this paper, I condition my analysis to trips 50 miles or fewer as only a few trips in the dataset extend well beyond. Figure 1 and Table 1 display the frequencies and cumulative frequencies of the trip lengths (miles) in the data set. The survey also collects individual characteristic information about each traveler such as their age, income, marital status, household size, home ownership, car ownership and the make of the vehicle they own. Table 2 lists summary statistics information about the individuals and their household in the data set.

Table 1: Cumulative Distribution of Trip Length (miles)

Miles	5	10	15	20	25
Freq.	61.6%	79.1%	87.5%	92.4%	95.5%
Miles	30	35	40	45	50
Freq.	97.3%	98.4%	99.2%	99.7%	99.8%

Table 2: Summary Statistics

		Age	Income	Temperature (F°)				Trip Miles (miles)				Home
MSA	Population	Avg	Avg	Med.	Avg	10%	90%	Med.	Avg	10%	90%	Avg
New York	9,821,147	50	106	57	56	32	77	2.9	6.2	0.3	17.1	59%
Los Angeles	6,434,177	47	101	67	64	57	69	2.9	6.0	0.4	16.4	53%
Chicago	4,653,591	48	98	52	50	22	73	2.9	6.1	0.4	16.9	62%
Dallas	3,654,402	47	96	67	64	44	85	3.6	6.9	0.6	18.4	59%
Washington	3,320,895	46	122	59	57	35	79	2.8	5.9	0.3	16.4	57%
Houston	3,198,729	47	102	70	68	52	84	3.6	7.0	0.6	19.1	60%
Philadelphia	2,915,178	50	91	57	56	32	78	3.4	6.3	0.4	16.5	62%
Miami	2,912,751	52	84	79	77	68	84	3.2	5.9	0.5	15.1	59%
Atlanta	2,868251	47	89	63	61	43	80	4.0	7.2	0.6	18.8	59%
Boston	2,572,454	48	102	54	51	29	74	2.6	5.8	0.3	15.7	42%
San Fran.	2,371,803	47	128	61	58	49	63	2.4	5.7	0.3	15.9	54%
Phoenix	2,182,537	51	87	75	72	54	93	3.5	6.9	0.6	19.1	62%
Seattle	1,997,545	47	108	51	52	40	68	3.2	5.9	0.4	15.4	41%
Detroit	1,980,465	49	87	52	51	25	74	4.0	7.3	0.6	19.9	64%

I use the most recent survey conducted in 2017 which documents the trips of households from June 2016 to May 2017, and I supplement the NHTS dataset with collected information on local car ride-sharing fares, bus and train metro fares, bike ride sharing fares and parking costs for all major cities. To account for consumer preferences for hospitable traveling environments in the summer and winter, I also collect average seasonal temperature data for each of the 52 MSA's for all four major seasons. This both captures variation in seasonal trip temperatures a traveler experiences within a city for winter, fall, spring and summer and variation across different regions where climate differences may impact the mode market share. Table 2 lists out the average temperature for 10 major cities and the 10% and 90% percentile temperature over the course of the seasons. Table 3 describes the mode demand for some of the major MSA's. The two most common form of transportation modes chosen in the data are driving and walking, which both represent 97.2% of all chosen modes.

Figure 1: Distribution of Trip Miles

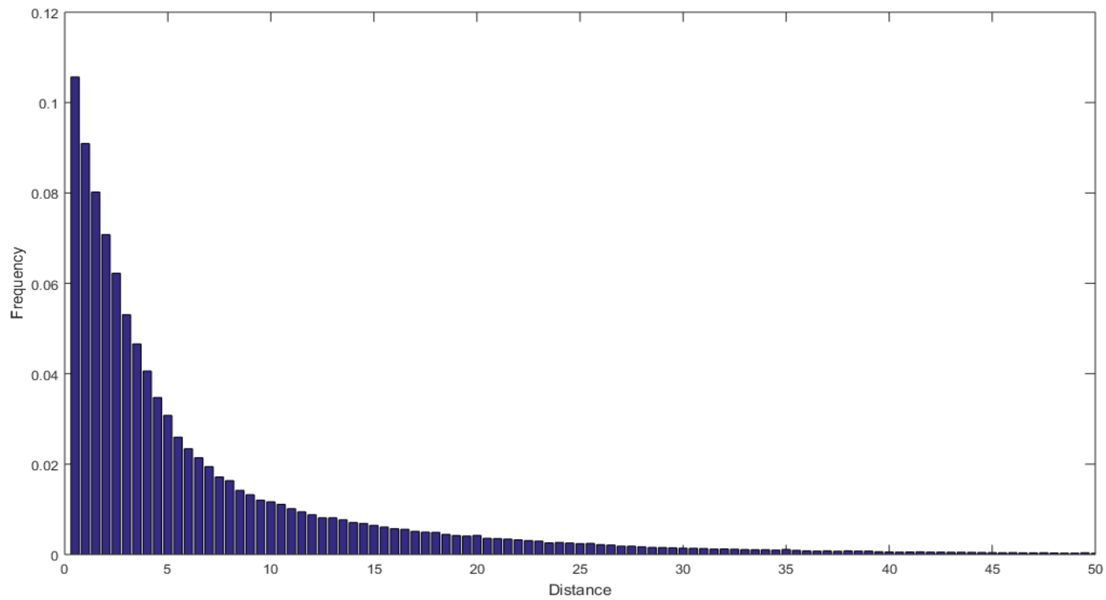


Table 3: Mode Demand Distribution by MSA

	Walking	Bicycle	Car	Metro
New York	20.3%	1.8%	72.7%	5.2%
Portland	16.0%	2.4%	78.3%	3.3%
Seattle	15.5%	1.7%	79.4%	3.4%
Washington	26.0%	1.6%	67.0%	5.4%
San Francisco	22.2%	2.1%	70.3%	5.4%
Boston	19.5%	2.1%	73.6%	4.9%
Pittsburgh	13.7%	0.2%	84.4%	1.7%
Chicago	14.3%	2.2%	80.0%	3.5%
San Diego	16.7%	1.4%	80.8%	1.1%
Los Angeles	13.2%	2.0%	83.2%	1.7%
All	10.8%	1.0%	86.4%	1.8%

American Community Survey

Another survey dataset used in the discrete choice analysis is of average commute times and commuter mode shares from the American Community Survey (ACS) collected by the Census Bureau. The Census Bureau conducts periodic annual surveys in the ACS that span topics such as current and past occupations, educational attainment, commuting, renting and home ownership, etc. which describe the characteristics of the U.S. population, local and state governments, and businesses. The Bureau compiles this data for cities, counties, and MSA's regions. Among the questions related to the workers commute, the American Community Survey (ACS) asks respondents about their primary workplace location and average travel time to work. It also tracks the transportation mode that commuters take by car, bus, bicycle and rail. I use collected data from the survey on population and the number of vehicle commuters in each MSA.

Determining Damages from Electric Load

For marginal emission factors from electricity demand, Holland et al. (2020) estimate the emissions that result from electricity use by determining which power plants are called upon to meet the load and how much additional emissions is being produced by those power plants as a result of the increased electricity usage. The electricity grid in the contiguous United States consists of three main "interconnections": Eastern, Western, and Texas that are segmented from one another in such a way that electricity flows freely from source to user within each interconnection but due to transmission constraints a quite limited amount of electricity flows across interconnections. Hence pollution damages measuring emissions per kWh from load demand are modeled for each interconnection separately. Therefore, this estimation strategy assumes that an e-scooter charged at any county within a given interconnection has the same marginal emission factors as an another e-scooter charged at any other county within the same interconnection. The authors in Holland et al. (2020) find that the marginal damage estimate over the sample for the eastern connection is \$0.073 per kWh where coal power plants are a have a larger share of power production. And in the West and Texas were renewables are a larger share of production, the marginal damages estimated over the sample are much lower: \$0.025 per kWh in the West and \$0.032 per kWh in Texas.

AP2 Model: Determining Damages from Local Air Pollution

Environmental benefit is the difference in damages from driving a gasoline vehicle and charging an electric scooter over the same driven miles. Estimates of marginal damages per unit of a given local pollutant are provided from the AP2 model. The AP2 model is an integrated assessment model model that calculates the local damage of emissions for all counties in the United States from that of baseline levels of emissions at 10,000 distinct sources. The marginal damage estimates from the AP2 model are calculated in a three step procedure of first connecting reported emissions (USEPA 2014) from all sources to estimates of ambient concentrations by means of an air quality model. Then connecting the ambient concentrations outputted from the air quality model into physical effects. And lastly connecting those physical effects into monetary damages. I use county level marginal damage estimates from Muller et al which I map into an MSA value. Table 4 lists the marginal damages for 5 major pollutants for the highest and lowest MSA's.

Table 4: Marginal Damages Per Ton by Pollutant (in thous.)

Name	MSA	NH3	NOX	PM25	SO2	VOC
Los Angeles	31080	$1,257	$433	$1,491	$753	$68
Washington	47900	$860	$77	$1,036	$220	$47
Philadelphia	37980	$852	$67	$1,073	$189	$49
New York	35620	$880	$67	$990	$167	$45
Chicago	16980	$655	$77	$754	$199	$34
San Francisco	41860	$513	$80	$701	$188	$32
San Diego	41740	$295	$126	$523	$360	$24
St. Louis	41180	$39	$14	$68	$45	$3
Jacksonville	27260	$45	$10	$70	$33	$3
Sacramento	40900	$33	$13	$63	$38	$3
Birmingham	13820	$34	$10	$54	$31	$2
Dallas	19100	$32	$9	$50	$30	$2
Houston	26420	$31	$8	$54	$28	$2
Virginia Beach	47260	$25	$8	$47	$28	$2
Oklahoma City	36420	$30	$10	$49	$12	$2

Traffic Congestion Data

In addition to calculating the environmental benefits of of e-scooters, I also assess the potential congestion benefits. Congestion, the cost of idled vehicle time on the road due to traffic, varies at different times of the day and on different parts of the road network and is directly related to the supply and the demand for road space. A narrow road, deep in a city center at rush hour, will be heavily congested (large demand, small supply) in comparison to a wide highway in the late evening (small demand, large supply). I gathered congestion data from the Texas A&M Transportation Institute and INRIX about the cost of traffic congestion in 52 major U.S. cities. The Transportation Institutes congestion data ranges from 1982 to 2017 and its estimates are also derived from INRIX's real-time GPS probe which uses traditional real-time traffic flow information, and hundreds of market-specific criteria that affect traffic such as - construction and road closures, real-time traffic incidents, weather forecasts and school schedules, sporting and entertainment events– to provide the most accurate picture of current traffic flows. Congestion rates are calculated based on local factors regarding speed of vehicles during peak and off peak hours on roads and highways in and out of the city, the total number number vehicle rider, and road bottlenecks.

Trip Cost and Time Data

Using the NHTS survey data, I construct two mode specific characteristics that describe a trips utility, the length of time of the trip $t_{i,j}$ and its cost $p_{i,j}$ for an individual i's trip for mode j. Since the cost and time of a mode trip are not truly observed variables in the data when consumers are weighing mode options it therefore has to be estimated based individual and local factors such as local fares, vehicle ownership, speeds and the trips distance range. Table 5 lists summary statistics for the estimated trip cost and time variables.

Table 5: Summary Statistics of Trip Cost and Time

Cost ($\$p$)	Walking	Bike	Car	Metro	Distance
Median	0.00	3.50	1.16	2.25	3.34
Mean	0.00	4.44	1.76	2.16	6.49
Stdv	0.00	2.19	2.50	0.48	8.12
Max	0.00	8.5	108.3	3.25	50.00
Time (t hrs)	Walking	Bike	Car	Metro	Distance
Median	1.33	0.48	0.16	0.34	3.34
Mean	2.58	0.93	0.30	0.68	6.49
Stdv	2.23	1.16	0.37	0.88	8.12
Max	19.99	7.14	2.93	5.0	50.00

For vehicle travel, I calculate the cost based on local gasoline prices over the distance of the trip. For fuel efficiency, since there are 436 different models of vehicles in the dataset, MPG estimation for vehicle use is based on vehicle type where sedan's have the highest MPG (24 MPG) and truck's the lowest (16 MPG), see Table 6. The most common vehicle type in the sample is sedans at almost 50% with SUV's at 29% (18 MPG) being second. Since many urbanities do not own a personal vehicle and rely more on taxicabs/ridesharing, I use UberX fare data on initial starting fares and per mile cost to price the cost of a vehicle trip for non-vehicle owners [2]. To account for parking cost

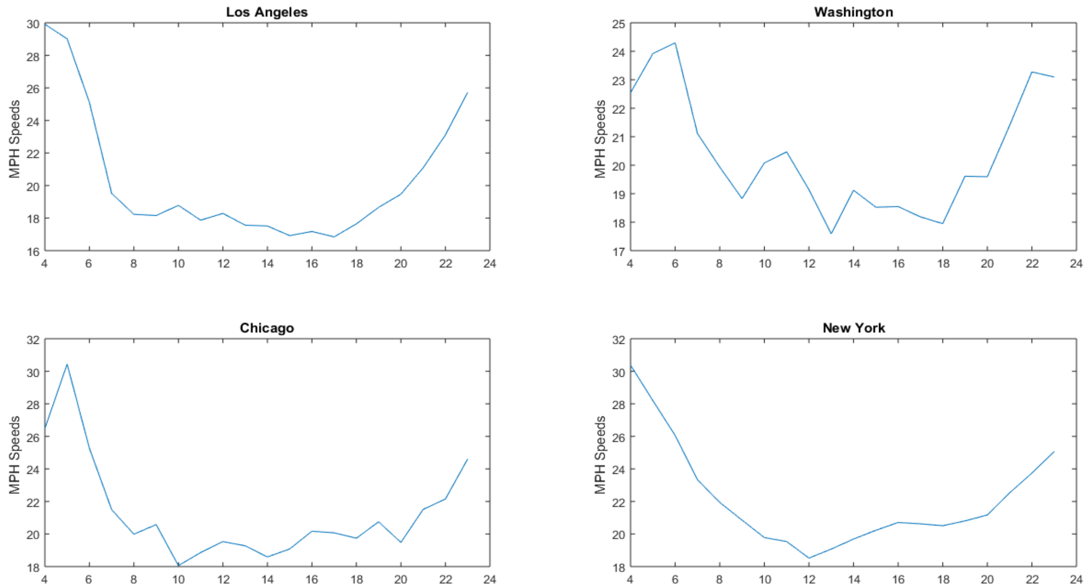
[2] I use data collected from Prateek Agrawal from the site the Intelligent Economist

in vehicle travel, I use collected data on monthly parking fares [3] which I convert to a daily fare. I assume a 15% probability that a consumer will need to park on their trip and I adjust the consumers cost of vehicle travel with the expected cost of parking on a trip, $E[C_m] = p * C_m + (1-p) * 0$, where p is the probability someone will park on a trip and C_m is the cost of parking on any random trip in city m. Because in some cities free parking is highly scare and in others more abundant, I only factor in expected parking costs for only the upper quartile of urbanely dense cities (e.g. New York, Washington, Boston, Chicago) and exclude the cost from less urbanely dense cities (e.g. Oklamaha City, Grand Rapids, Raleigh). For vehicle time of travel, using the NHTS, I model MPH for vehicle travel based on the hourly time of day of the trip for each city – this accounts for variation in congestion throughout the day. Though not directly observable in the data, I identify MPH speeds for each of the 24 hours of the day by conditioning on trips in the sample where the start time and end time of the trip was within the interval of the whole hour, e.g. vehicle trips between 9:00 am and 9:59 am. I then compute speeds by dividing distance of the trip by the length of time and averaging across all the trips that occurred only within the hour. This procedure identifies MPH speeds for trips that occurred during the hour. Figure 2 shows the MPH speeds for 4 major metropolitan areas across different hours of the day for Los Angeles, Washington, Chicago, and New York. I omit speeds between 1 am and 3 am from the graph due to lack of available data of trips during those hours. In all major cities vehicle speeds are highest during the early morning and late in the evening and speeds are the lowest during rush hour congestion.

For metro and bike costs, I use single fare data collected for each of the MSA's that I have collected from the websites of bike share and metro operators. Metro speeds are calculated from the NHTS and are based on average local MPH speeds for public transportation – Table A2 lists the metro speeds for each of the cities. For bike and walking speeds I use assume a 7 MPH and 2.50 MPH speed respectively. Table 7 lists single ride and annual fares for each cites local bike and public metro fares. In every city in the sample there is a major form of public transportation in either bus and/or rail system that consumers have access to. And for every city there is a designated bike sharing program that is either fully owned and operated by the city or operated

[3]Data is MSA level parking fare data collected by the City Observatory from the park listing site ParkMe.

Figure 2: MPH Vehicle Speeds during the Day



in conjunction with a joint-ventureship with a private business such as the Citi Bikes in New York city or Capital Bikes in Washington, DC.

3 Empirical Model of Transportation Utility and Estimation of Emission and Congestion Benefits

Standard Multinomial Logit Model for mode Transportation

I use a model that is based on McFadden's 1974 random utility framework, in which consumers of a mode of travel aim to maximize their utility of travel. This utility is unobserved and for each alternative is assumed to be a linear function of various independent variables and an error term. The utility of **individual** i using transportation **mode** j is:

Table 6: Vehicle Type and Model Summary Statistics

Vehicle Type	Vehicles	Frequency
Sedan	396,931	49.9%
SUV	229,466	28.9%
Van	60,463	7.6%
Pickup truck	108,303	13.6%
Model	**Vehicles**	**Frequency**
F-Series pickup	11,159	4.4%
C, K, R, V-Series Silverado	7,617	3.0%
Camry	7,067	2.8%
Accord	6,466	2.5%
Civic/CRX Del Sol	5,076	2.0%
Ram Pickup	4,811	1.9%
CR-V	4,726	1.8%
Corolla	4,398	1.7%
Prius	3,688	1.4%
Escape	3,213	1.3%

$$U_{ij} = V_{ij} + \epsilon_{ij}.$$

The deterministic component of the utility function, V_{ij}, is assumed to be linear in unique characteristics about the consumer and the mode of travel,

$$V_{ij} = \gamma' x_{ij} + \phi_j' z_i + \eta'(z_i x_{ij}),$$

where x_{ij} represents characteristic variables that vary across mode choices for individual i such as the price and time of a trip. And where z_i represents characteristics of the individuals that are constant across choices such as an individuals age and income. The product of the two $x_{ij}z_i$ represents the interaction between the variables that vary by mode choice and individual specific characteristics. The consumers preference shock for mode j, ϵ_{ij}, has a standard Type I extreme value distribution, $f(\epsilon_{ij}) = e^{\epsilon_{ij} - e^{\epsilon_{ij}}}$.

Table 7: Bike and Metro Fares by City

City	Bike Share Name	Single	Annual	Metro Name	Single	Annual
Los Angeles	Metro Bike Share	1.75	150	LA Metro	1.75	122
New York	Citi Bike	3.5	180	MTA	2.75	116.5
Sacramento	Biketown	4	60	SacRT	2.5	110
Chicago	Divvy Bikes	3.3	108	CTA	2.25	100
Portland	Biketown	7	99	Portland Metro	2	100
Denver	Denver B-cycle	7	80	RTD	3	99
Seattle	Seattle DOT	8	85	Seattle Metro	2.75	99
Atlanta	Relay Bike Share	3.5	120	MARTA	2.5	95
Philadelphia	Indego	4.5	156	SEPTA	2.5	91
San Francisco	Ford GoBike	2	149	SFMTA	2.5	91
Charlotte	Charlotte B-cycle	8	100	CATS	2.2	88
Tampa	Coast Bike Share	8.5	99	HART	2	85
Boston	Blue Bikes	3.5	109	MBTA	2.5	84.5
Nashville	Nashville B-cycle	5	50	NMTA	2	84
Washington	Capital Bikeshare	2	85	WMATA	3.25	81
St. Louis	St.L. Dockless Bike	5	180	St.L. Metro	2.25	78

The simplest and most common specification that will be used for this paper will be that of a two factor utility model where the consumers utility is dependent on the price p and travel time t of the travel mode, $x_{ij} = (p_{ij}, t_{ij})$ $\gamma = (\alpha, \beta)$. The random utility of the consumer represented as linear across price and characteristics of a mode trip as,

$$U_{ij} = \alpha_i p_{ij} + \beta t_{ij} + \epsilon_{ij}.$$

I also allow for variation in the consumers sensitivity to price α_i and assume that it is a function of the consumers income level, I_i,

$$\alpha_i = \alpha_0 + \alpha_1 I_i.$$

Varying sensitivity to price with respect to income is equivalent to interacting price with income in the consumers random utility,

$$U_{ij} = \alpha_0 p_{ij} + \beta t_{ij} + \alpha_1 I_i p_{ij} + \epsilon_{ij}.$$

Given the mode alternatives in their choice set consumer i will choose transportation mode j if and only if it maximizes his utility among all possible choices. This can be expressed as,

$$y_i = j \quad \text{if} \quad U_{ij} \geq U_{i,m}, \quad \forall m \in \{1, 2, ..., J\}$$

where y_i is a discrete integer function of the choice set that represents the availiable choices. The four possible ex-ante mode choices are,

$$y_i = \begin{cases} 1, & \text{walk} \\ 2, & \text{bike} \\ 3, & \text{car} \\ 4, & \text{metro} \end{cases}$$

The probability that individual i chooses transportation mode j is,

$$P_{ij} = \Pr(y_i = j) = \Pr(U_{ij} = \max[U_{i1}, ..., U_{iJ}]) = \frac{e^{V_{ij}}}{\sum_{m=1}^{J} e^{V_{i,m}}}$$

The coefficients of the model can therefore be interpreted through their impact on the log–odds ratio of each alternative to the base case of the walking mode choice.

Calculating Air Pollution Damages

The environmental benefits of an e-scooter arises from the reduced damages relative to the gasoline vehicle it replaced for a trip. I take the same procedures taken in Holland et al. (2016)

in calculating this benefit for vehicles. First, I determine how much emissions are produced per mile for both gasoline vehicles and e-scooters. Second, using the discrete choice model I estimate the attributable demand for e-scooters as a direct result of the substitution from gasoline vehicles. And then lastly map those total emissions from vehicle and e-scooter demand into nominal dollar damages, accounting for the fact that both emissions and marginal damages of those emissions vary by location. Since metropolitan area is the closest identification for location for survey respondents in the NHTS, in my calculations MSA is the smallest unit of location. For damages estimates that are at the county level I aggregate up to the MSA level by choosing the most populace county for the MSA value.

I consider damages from five major pollutants: CO_2, SO_2, NO_x, $PM_{2.5}$, and VOCs. These pollutants account for the majority of air pollution damages that are emitted from the tailpipes of gasoline vehicles.

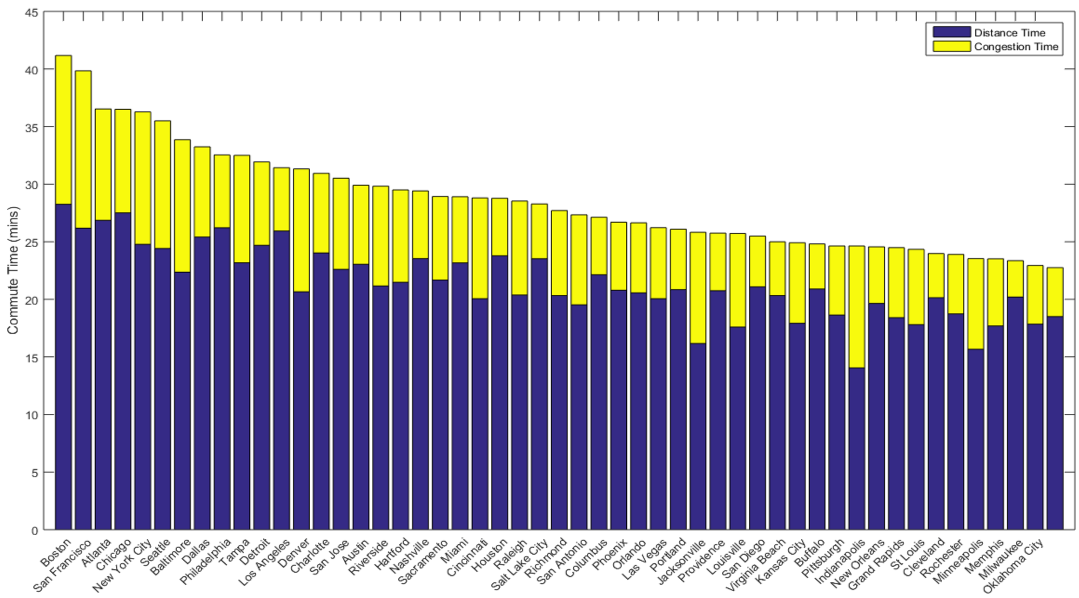
To determine the emissions per mile for gasoline vehicle, I use Tier 2 emission standards of 370.3 gram per mile for CO_2, 0.05 grams per mile for NO_x, 0.188 grams per mile for VOCs, 0.013 grams per mile for SO_2, and 0.0041 grams per mile for $PM_{2.5}$. For e-scooters, determining emissions per mile I use a standard 250 Watt motor electric scooter and calculate the total load needed for an e-scooter per mile. I use the marginal damage per kWh estimates for load estimated by Holland et al. 2018 of $0.073 per KWh for the eastern connection, $0.025 per KWh for the western connection, and $0.032 per KWh for the Texas ERCOT connection.

After calculating emissions for both gasoline vehicles and e-scooters, I then map emissions into damages. For CO_2, I use the EPA social cost of carbon of $41 per ton. For local pollutants, I use estimates provided from the AP2 model, an integrated assessment model that calculates damages per unit of a given local pollutant in each county (see data section). By multiplying emissions per mile with damages per unit emitted, and then aggregating across pollutants I obtain the full damages per mile for each gasoline vehicle and each electric scooter in each county.

Estimating Congestion Cost

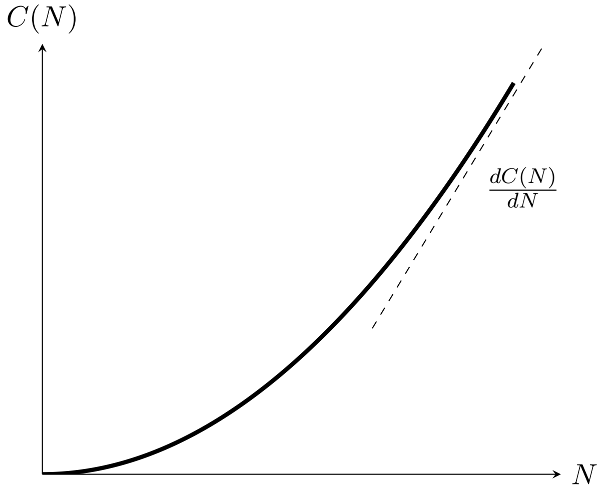
Congestion varies across cities due to local traffic conditions and factors such as the number of registered vehicle riders, the ordinance speed limits, number of traffic lights stops, traffic accident rates, all influence the variation in congestion from city-to-city. Figure 3 shows the breakdown of average commute times attributable to congestion cost by city. Though congestion is theoretically an equilibrium outcome of vehicle road demand and road supply, the approach taken in this paper is a much simpler and straight forward approach to computing marginal congestion that is empirical and data dependent and accounts for local heterogeneity in each cities congestion function.

Figure 3: Congestion as part of Average Daily Commute Times (mins)



I model congestion for each city as a strictly increasing convex function, $C(N)$, of its total daily vehicle commuters, N, holding all other local factors constant as in Figure 4. The slope of the congestion function is marginal congestion, $\frac{dC(N)}{dN}$. The assumption is that short-run variation in congestion is attributable to changes in the number of daily vehicle commuters for each city. Because many urban dense cities experience greater changes in congestion once they have hit their capacity constraint in vehicle commuters, this creates a greater quantities of congestion growth for small changes in the number of vehicle riders causing the congestion function to be more convex.

Figure 4: Congestion Function'



Marginal congestion can be estimated with either a first or second order approximation.

Figure 5 plots the congestion functions, $C(N)$, of the MSA's with respect to the number of vehicle commuters, N, in its metropolitan area where each city has it's own congestion function. One clear observation about the congestion functions is that there is a monotonically increasing relationship between vehicle riders and a city's congestion. Moreover that metropolitan areas with large population and that are urban dense such as Washington and New York have higher levels of annual congestion than less populated, less dense cities such as Buffalo or Kansas City. An additional observation is that while overall congestion levels might be lower for smaller populated cities, given the availability of roads and the overall demand for road space from the cities population, a city can experience high levels of marginal congestion due to demand hitting its capacity constraint of available road supply causing high levels of congestion growth for small changes in vehicle ridership.

I collect historical congestion and vehicle rider data for the 52 MSA from the Texas A&M Transportation Institute and calculate the marginal congestion, $\frac{dC(N)}{dN}$, as a first order approximation with the exception of two MSA's that required a second order approximation. This approximation is done through a *localized* ordinary least squares regression over a window of the most recent 4-6 years around the point corresponding to the current number of commuting vehicles for a city, in effect a taylor approximation. Table A4 lists the estimations of marginal congestion for each of the MSA's.

4 Estimation & Identification

In order to estimate the conditional logit models, the data must be constructed in such a way that there are J observations for each individual i's trip. As there are 397k individual trips in our sample across 52 MSA's with complete information on all variables of interest respectively, this results in respective sample sizes of 1.5 million. I make several restrictions and modifications on the trips used for analysis. For some of my estimations I consider only trips 15 miles or less since walking and cycling may be unavailable or infeasible as a transportation mode for those traveling long distances that are 15 miles or more. I also combine bus and subway rail as single mode choice called "metro" transportation since they have similar characteristics, both in time of travel, once accounted for the walking to the subway station/bus stop, and the local metro fares. For individuals in metropolitan areas that may not own a personal vehicle, I set the cost of a vehicle ride as that of an Uber fare in their local city. I run several specifications of the multinomial logit model on different variables and condition on distance and trip purpose.

To estimate the model, I take the same approach as McFadden (1973) for logit models estimation and assume that every decision maker chooses their alternative independently and use maximum likelihood estimation. The probability of all decision maker choosing their actual choices is a vector of the actual outcomes and the parameters to be estimated. The likelihood function or joint distribution of the observed sample is,

$$L(\theta) = f(y_1, .., y_N) = \prod_{n=1}^{N} \prod_{j=1}^{J} P_{ij}^{y_{ij}}$$

Where $y_{ij} = 1$ if individual i chooses mode j and 0 otherwise.

The true parameter vector $\theta = (\gamma_1, ..., \gamma_k, \phi_1, .., \phi_m, \eta_1, .., \eta_p)$ that sets the gradient vector of derivatives to 0 maximizes this joint probability,

Identification

Since all parameters of the model are estimated jointly when maximizing the likelihood function, the parameters of the utility are identified since the dataset satisfies the order and rank condition. However in this section, I also provide some informal discussion on identification.

In this partial equilibrium model, prices for the modes are assumed to be exogenous. That is, consumers take the price of gasoline, metro fares and bike fares as given. This exogeneity identifies the cost parameter in the utility function.

Moreover, there are two types of characteristic variation in the data for cost and time: city level and individual level. Variation across cities includes differences in cost characteristics for gasoline prices, metro fares, bike fares and variation in MPH vehicle speeds. And within each city there is individual level variation in the distance of the trips resulting in different cost and travel times for each trip length. Variation in mode share as a result of consumers optimizing between cost and time for a trip identifies the mean value of time. And the use of a consumers income identifies the variation of the value of time for different consumers.

Estimating Reduction in Vehicle Mode Share

From the first order conditions from the likelihood function, I estimate $\hat{\theta} = (\hat{\gamma_1}, ..., \hat{\gamma_k}, \hat{\phi}_1, .., \hat{\phi}_m, \hat{\eta}_1, .., \hat{\eta}_p)$ and calculate the probability that individual i chooses transportation mode $j \in \{1, 2, 3, 4\}$ **prior** to the introduction of electric scooters ,

$$\widehat{P}_{ij} = \frac{e^{\hat{\gamma}' x_{ij} + \hat{\phi}_j' z_i + \hat{\eta}'(z_i x_{ij})}}{\sum_{m=1}^{4} e^{\hat{\gamma}' x_{im} + \hat{\phi}_j' z_i + \hat{\eta}'(z_i x_{im})}}$$

For a city with mass population M, the market share for a transportation mode j would be the average of all the cities populations probability of using that mode,

$$s_j = \frac{1}{M} \sum_{i=1}^{M} \hat{P}_{ij}.$$

I then introduce e-scooters to the choice set of options a user could take and using the same estimates for $\hat{\theta}$ recalculate the probabilities that individual i chooses transportation mode j **after** the introducion of e-scooters as a possible mode. Because electric scooters and bikes share similar product qualities – both being small, outdoor transportation devices – I make the assumption that riders of electric scooters have the same marginal utility with respect to certain mode attributes as that of bike riders and thus have the same coefficient values in the utility function of consumers for certain types of mode characteristics. The probability an individual rides mode $j \in \{1, 2, 3, 4, 5\}$ with electric scooters in the choice set is,

$$\widetilde{P}_{ij} = \frac{e^{\hat{\gamma}' x_{ij} + \hat{\phi}_j' z_i + \hat{\eta}'(z_i x_{ij})}}{\sum_{m=1}^{4} e^{\hat{\gamma}' x_{im} + \hat{\phi}_j' z_i + \hat{\eta}'(z_i x_{im})} + \underbrace{e^{\hat{\gamma}' x_{i5} + \hat{\phi}_2' z_i + \hat{\eta}'(z_i x_{i5})}}_{\text{e-scooter}}}.$$

Thus the reduction in market share of vehicles is

$$\tilde{s}_{car} - \hat{s}_{car} = \frac{1}{M} \sum_{i=1}^{M} (\widetilde{P}_{i,car} - \widehat{P}_{i,car}),$$

where M is over all the surveyors in the city population. The product of this reduction in market share with the total number of vehicles riders N for a particular city is the reduction in vehicles taken off the road as $dN = (\tilde{s}_{car} - \hat{s}_{car})N$. After computing marginal congestion, I map this reduction in vehicles on the road for commutes into marginal congestion time for all 52 cities.

I calculate for each city i the marginal congestion time benefit is,

$$dC_i = \frac{dC_i}{dN_i}(\tilde{s}_{i,car} - \hat{s}_{i,car})N_i.$$

5 Results

I estimate several multinomial logit model estimations in Table 8 on two main mode specific characteristics that describe a trips utility, the length of time of the trip $t_{i,j}$ and its cost $p_{i,j}$ for an individual i's trip as well individual specific characteristics. Summary statistics for the cost and time in the data sample can be found in Table 5. I estimate three models and I find in all the models that the sign of both the cost and trip time coefficient estimates are negative suggesting consumers are minimizing their disutilitiy of travel for cost and time. In addition, the models coefficient value also tell us the consumers sensitivity to time and cost in their utility. In model 1, I run the most basic model on trip cost and trip time and I find the mean marginal utility of time for the entire sample to be \$3.69 with a marginal cost of \$0.25. The model has a McFadden R^2 of 0.28 which means the simple two factor model generates a good overall fit of the data. With walking as the base reference, the mode specific constant indicates that consumers have a negative mode preference to biking and taking public transportation and a positive preference to car rides.

The way to measure the value of time in this random utility framework is as defined by Train (1980), Hensher, Greene (2003), Armstrong, Garrido, Ortúzar (2001) and Hess, Bierlaire, Polak (2005) and other papers in the transportation literature is by means of calculating the marginal rate of substitution between between cost and time – that is, the extra cost that a person would be willing to incur to save an hour of time. The total derivative with respect to changes in time and cost is set to zero to solve for dp/dt to find the change in cost that keeps utility unchanged for a change in time:

Table 8: Multinomial Logit Models

	(1)			(2)			(3)		
	Bike	Car	Metro	Bike	Car	Metro	Bike	Car	Metro
Constant	-2.68	0.08	-2.91	-2.71	-0.02	-3.00	-2.68	-0.07	-0.58
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.12)	(0.04)	(0.08)
Trip Cost (α_0)	-0.25	-0.25	-0.25	-0.27	-0.27	-0.27	-0.29	-0.29	-0.29
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Trip Time (β)	-3.69	-3.69	-3.69	-3.70	-3.70	-3.70	-3.71	-3.71	-3.71
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Price $\cdot$ Income (α_1)				0.32	0.32	0.32	0.44	0.44	0.44
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Mode Temp. Dev. (ϕ)				-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age							-0.02	0.01	-0.02
							(0.001)	(0.0003)	(0.001)
Travelers							-0.47	0.12	-0.70
							(0.02)	(0.01)	(0.02)
Health							0.01	-0.01	-0.02
							(0.001)	(0.0003)	(0.001)
Log-Likelihood	-135,380	-135,380	-135,380	-135,250	-135,250	-135,250	-132,230	-132,230	-132,230
N observations	389,683	389,683	389,683	389,683	389,683	389,683	389,683	389,683	389,683
McFadden R^2	0.28	0.28	0.28	0.29	0.29	0.29	0.30	0.30	0.30
Value of Time	\$14.61	\$14.61	\$14.61	\$15.32	\$15.32	\$15.32	\$15.37	\$15.37	\$15.37

$$dU_{ij} = \alpha dp_{ij} + \beta dt_{ij} = 0$$

From this the marginal rate of subsitutiton can be solved which is the ratio of the marginal utility of time over the marginal utility of cost,

$$VoT = MRS = \frac{dp}{dt} = -\frac{\beta}{\alpha}.$$

In model's 2, I re-estimate the model but allow for heterogeneity in the consumers price sensitivity to the cost of a trip with respect to income. I find that for an average household income of $98,000 that the value of time for traveling consumers is $15.32. Table 9 lists the value of time estimates for varying household incomes in the sample. This implied value of travel time is lower and in line with that of the median wage rate in the U.S. of $19.90, i.e. which represents the value of an hour of work of time. In a recent paper on the value of time by Buchholz, Doval, Kastl, Matejka, Salz (2020) on large ride-hail platform, where drivers bid on trips and consumers chose between a set of rides with different prices and waiting times, the authors found a net value of travel time of $13.47. Another benchmark value provided by the 2019 Texas A&M Transportation Institute Urban Mobility Report valued an hour of travel time at $17.91 in 2016. Their methodology for deriving the value of delay time was estimated using a speed choice model on a small number of toll roads of commuters used in the transit systems in the state of Texas in 1997. The initial value of time estimate in the study of $11.98 has been CPI adjusted since the study. In the model I also attempt to capture seasonality in mode demand and variation in temperature environments across different cities by including a temperature deviation from 70 degrees fahrenheit for each of the respective modes. I find that for every 1 degree deviation in temperature from 70 degrees Fahrenheit, the utility of the consumer drops by -0.01. I estimate a similar model but where temperature deviation from 70 degrees Fahrenheit is the same for all modes in model 4 in table 10 and I find that for greater deviations from 70 degree the less likely the consumer demands bike travel and the more likely they are to demand car and metro travel.

In model 3, I estimate a full model that conditions a modes utility on the consumers age, the number of travelers accompanying the surveyor on the trip, and a self-assessment score of the surveyors overall health that ranges from 0 to 100, where 100 denotes great shape and health. I find that the older the consumers is the more likely they are to demand vehicle travel and the less likely they are to demand bike and metro travel with walking as a reference mode. That the more individuals accompanying a consumer on a trip the more likely they are to take vehicle travel over bike and metro travel. And that the healthier the individual is the more likely they are to bike over car and metro travel. I find the value of time estimate on the full model rises to $15.37.

Table 9: Value of Travel Time for Different Income Brackets

Household Income	VoT
$50k$	\$14.10
$60k$	\$14.35
$70k$	\$14.60
$80k$	\$14.86
$90k$	\$15.12
$100k$	\$15.40
$110k$	\$15.69
$120k$	\$15.99
$130k$	\$16.30

From all the full model estimated, I also find that the marginal of cost a trip, α, is 0.29. The marginal cost is directly proportional to the elasticity of demand for each mode. The higher the marginal cost is the more substitutable the mode options are between one another and the more sensitive each mode demands share is to changes in own price. To better understand the consumers marginal cost of a trip, I map the marginal cost of a consumers trip into a price elasticity of demand derived from the differentiation of the market share probabilities for each of the modes $\frac{\partial s_j}{\partial p_j} = \frac{\partial V_{ij}}{\partial p_j} s_j(1 - s_j)$,

$$\epsilon_j = \frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = (1 - s_j)p_j\alpha.$$

From Table 11, we find that the modes of transportation all have elasticities that are less than 1 which implies that demand curve for each of the modes is inelastic. Of the three non-walking modes, vehicle demand is the most inelastic, with metro demand second and bike demand being the most elastic with an elasticity greater than 1 for several cities. This is supported by the fact that for longer distance trips, vehicle demand is non-substitutable with other modes of travel and therefore the most demand inelastic.

Next I measure the goodness of fit of the multinomial logit model by estimating model (3) on

Table 10: Multinomial Logit Models

	(2)			(4)		
	Bike	Car	Metro	Bike	Car	Metro
Constant	-2.71	-0.02	-3.00	-2.50	0.00	-3.12
	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)
Trip Cost (α_0)	-0.27	-0.27	-0.27	-0.27	-0.27	-0.27
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Trip Time (β)	-3.70	-3.70	-3.70	-3.69	-3.69	-3.69
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Price Income (α_1)	0.32	0.32	0.32	0.33	0.33	0.33
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Mode Temp. Dev. (ϕ)	-0.01	-0.01	-0.01			
	(0.001)	(0.001)	(0.001)			
Trip Temperature. Dev. (ϕ_j)				-0.02	0.01	0.01
				(0.0018)	(0.0005)	(0.0012)
Log-Likelihood	-135,250	-135,250	-135,250	-135,150	-135,150	-135,150
N observations	389,683	389,683	389,683	389,683	389,683	134960
McFadden R^2	0.29	0.29	0.29	0.29	0.29	0.29
Value of Time VoT	$15.32	$15.32	$15.32	$15.36	$15.36	$15.36

the entire sample of MSA trips and then comparing the models predicted probability for each mode choice to that of the actual mode distribution for that MSA from the sample. Figure 3 plots the predicted probability from the estimated model to that of the actual distribution of mode travel for all 52 MSA's on all and commute trips.

After having compared the relative fitness of the multinomial logit model predictions to the actual distribution of mode demand for each of the MSA's, I then introduce electric scooter as an alternative to the choice set of traveling consumers and recalculate the probabilities for the existing modes and the probability of e-scooter adoption for each of the MSA's. Table 13 shows all the cities most likely to adopt e-scooters. I find that larger, more densely urban cities such as New York, Washington, and San Francisco are more likely to adopt electric scooters than less densely populated cities. New York showed the highest rate of adoption at 1.93% with Washington second at 1.76%.

Table 11: Mode Demand Elasticities by MSA

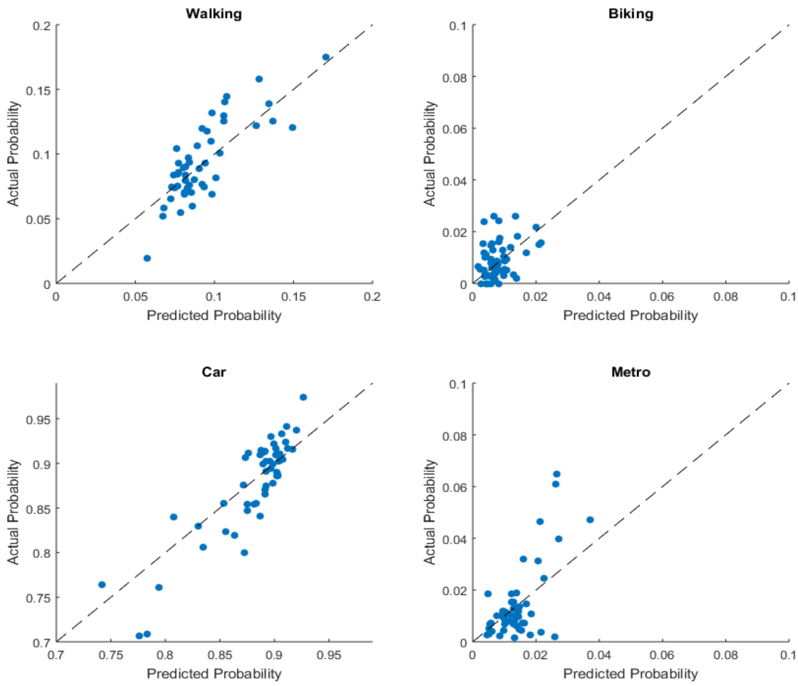
Distance	ϵ_{walk}	ϵ_{bike}	ϵ_{car}	ϵ_{metro}
New York	0.00	-1.00	-0.55	-0.68
Boston	0.00	-0.97	-0.51	-0.62
Washington	0.00	-0.57	-0.46	-0.80
San Francisco	0.00	-0.57	-0.35	-0.61
Chicago	0.00	-0.94	-0.24	-0.56
Seattle	0.00	-2.30	-0.24	-0.68
Philadelphia	0.00	-1.29	-0.18	-0.64
Portland	0.00	-1.98	-0.16	-0.51
Pittsburgh	0.00	-0.58	-0.15	-0.64
San Diego	0.00	-0.86	-0.15	-0.64
New Orleans	0.00	-2.31	-0.14	-0.32
Sacramento	0.00	-1.12	-0.14	-0.64
Denver	0.00	-1.97	-0.13	-0.77
San Jose	0.00	-0.56	-0.13	-0.64
Baltimore	0.00	-0.57	-0.12	-0.48

Table 12: For a median trip of 3.34 miles

I then look at the change in market share estimates for vehicles before and after the introduction of e-scooters and calculate reduction in the vehicle market share attributable to the substitution from gasoline vehicle to electric scooter. Table A3 and Figure 6 lists and plots the market share reduction of vehicles by MSA as a result of the introduction of electric scooters as a mode choice. I find large cities where commuting by vehicle is a larger existing share of commutes have substantive percent drops of 1% and more in vehicle demand after the introduction of electric scooters.

The next stage is to map vehicle market share reductions for all the MSA's, into environmental and congestion benefits. First for environmental benefits, I convert the market share reduction into physical units of cars for each city. I then estimate the annual miles reduction for vehicle commute trips being displaced by electric scooter and its reduced emissions across all 5 pollutants (CO_2, SO_2, NO_x, $PM_{2.5}$). Using the same NHTS dataset, I estimate the frequency of short distance trips made by electric scooters for each of the major cities to calculate the miles displaced which then I

Figure 5: Actual vs Predicted Probabilities



$$U_{ij} = \phi_j + \alpha_i p_{ij} + \beta t_{ij} + \gamma|F_j - 70| + \phi_{1,j}Age + \phi_{2,j}Travelers + \epsilon_{ij}$$

convert into emissions. I do so by running a simulation on the distribution of trips provided by the model in the dataset. For the trips where an electric scooter is taken, I calculate the mean miles ridden for each city and then map those miles into emissions. Table 14 lists the distribution of trip miles made on an electric scooter for the major cities. Netting the emissions produced by the electric load of the electric scooter over the same miles, I then map the net emission benefit into nominal emission marginal damages produced from the AP2 model. I find that electric scooters produce a total environmental benefit of \$2.82 million annually across all 52 MSA's (Table A3).

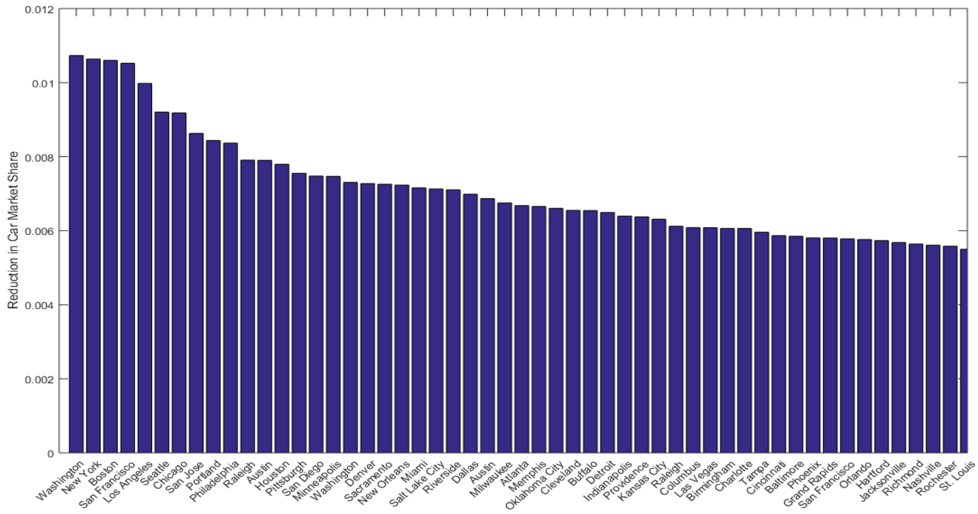
In order to estimate congestion benefits, I first estimate marginal congestion for each city. The estimation for marginal congestion is a localized first or second order approximation on the congestion function for each MSA (Table A4). I find that cities such as New York and Washington commuters experience a 0.28 hour and a 0.20 hour annual increase in congestion, respectively, for

Table 13: Ten Largest Markets and Ten Smallest Markets

City	Scooter Share	Reduction Car Share	Vehicle Commuter	Vehicle Reduction
New York	1.93%	1.06%	5,190,000	55,202
Washington	1.76%	1.07%	1,888,000	20,264
Boston	1.71%	1.06%	1,736,000	18,405
San Francisco	1.69%	1.05%	792,000	8,334
Los Angeles	1.54%	1.00%	5,905,000	58,926
Chicago	1.40%	0.92%	3,450,000	31,684
Seattle	1.39%	0.92%	1,543,000	14,201
Philadelphia	1.26%	0.84%	2,308,000	19,311
San Jose	1.18%	0.86%	1,024,000	8,836
Portland	1.15%	0.84%	900,000	7,593
City	Scooter Share	Reduction Car Share	Vehicle Commuter	Vehicle Reduction
Richmond	0.73%	0.56%	512,000	2,888
St. Louis	0.73%	0.55%	1,120,000	6,160
Virginia Beach	0.73%	0.55%	748,000	4,107
Rochester	0.73%	0.56%	359,000	2,004
Nashville	0.72%	0.56%	626,000	3,511
Cincinnati	0.71%	0.59%	853,000	5,007
San Antonio	0.70%	0.53%	1,025,000	5,440
Minneapolis	0.70%	0.52%	1,402,000	7,298
Louisville	0.68%	0.49%	587,000	2,873
Birmingham	0.60%	0.48%	420,000	2,006

every 1,000 gain vehicles commuters in the city. After computing marginal congestion for each city, I then map its vehicle reduction to find its annual congestion benefit for each driver. For example, in a city such as Portland, each driver experiences a 0.9 hour congestion reduction annually as a result of the 7.54k vehicle reduction caused by the introduction of electric scooters. In Boston, each driver experiences a 4.7 hour annual congestion reduction as a result of the 18.9k cars vehicle reduction. Lastly, I value this annual time saving each commuter gets at \$15.36 an hour to derive the congestion benefit. I find the total congestion benefit associated with electric scooters across all 52 MSA's at \$6.24B (Table A5).

Figure 6: Reduction in Vehicle Commute Market Share



The median congestion time savings per driver across all cities is 1.10 hours per years and an average of 2.63 hours. Since this time saving directly impacts the characteristic time variable of a trip t, which is a function of the market shares, s_j, of the modes this leads to an endogeniety problem in the estimation of market share. To account for total impact impact of electric scooters on congestion, I re-estimate the market share probabilities of each of the modes in a second iteration however with congestion reduced car vehicle trip times. I prorate the annual congestion time savings to a per trip time savings and lower the prior estimated vehicle travel time as a result of the congestion benefit, in effect increasing the MPH of the trip. This iterative step of estimating the congestion benefit and adjusting lower the time of a trip by the congestion benefit repeatedly done many times will lead to a converged mode share distribution, however a second iteratation is sufficiently close to those of the stable converged values. Table 15 displays the iterated results and I find that the total impact estimates of environmental benefit is \$2.75 million and the congestion benefit is \$6.01 billion, a slight reduction from the partial equilibrium estimates.

Table 14: Distribution of Trip Distances using an Electric Scooter

	Scooter Share	Mean (miles)	Median (miles)	5%th (miles)	95%th (miles)
New York	1.93%	1.16	0.82	0.12	3.22
Washington	1.76%	1.30	0.83	0.10	3.97
Boston	1.71%	1.33	1.02	0.11	3.46
San Francisco	1.69%	1.06	0.83	0.10	2.96
Los Angeles	1.54%	1.39	1.01	0.12	4.02
Chicago	1.40%	1.36	1.08	0.13	3.05
Seattle	1.39%	1.45	1.03	0.18	4.95
Philadelphia	1.26%	1.27	0.78	0.11	3.62
San Jose	1.18%	1.73	1.30	0.25	4.28
Portland	1.15%	1.23	1.01	0.11	4.24
Houston	1.10%	1.36	1.08	0.18	3.44
New Orleans	1.03%	0.81	0.56	0.03	1.88
San Diego	1.01%	1.14	0.80	0.15	3.21
Riverside	1.00%	1.53	1.27	0.20	3.25
Pittsburgh	0.99%	1.43	0.63	0.08	4.75

6 Conclusion

In this paper, I examine the reduction in air pollution damages and reduced vehicle traffic congestion times as a result of fewer vehicle use due the substitution to micromobility electric scooters. I focus on the importance of local factors in assessing pollution and congestion and the geographic heterogeneity of damages.

To assess these benefits I adopt a discrete choice framework that models the factors influencing consumers existing choice of travel. Several multinomial logit models are employed to analyze a large, trip level survey by the National Household Transportation Survey. My first set of results document the market share adoption rate of electric scooters as a mode choice for 52 major cities and the reduction in vehicle use as a result of the adoption. My second set of results documents the considerable heterogeneity in the environmental benefits and congestion benefits of a electric scooters.

I find a national value of travel time at $15.37 an hour and that the city adoption of electrified scooters can create an positive externality of $2.75 million in environmental benefits and $6.01 billion in congestion annually and I document the local heterogeneity in benefits across 52

Table 15: Total Effects

	Share (Partial) Scooter	Share (Total) Scooter	Congestion Benefit (thous)	Enviromental Benefit
Los Angeles	1.54%	1.38%	$2,371,648	$657,462
New York	1.93%	1.82%	$1,192,589	$436,063
Chicago	1.40%	1.32%	$765,727	$238,695
Philadelphia	1.26%	1.19%	$437,880	$105,289
Miami	0.98%	0.97%	$124,118	$104,316
Boston	1.71%	1.68%	$119,700	$69,915
Washington	1.76%	1.74%	$114,562	$134,334
Atlanta	0.87%	0.86%	$106,223	$44,071
Pittsburgh	0.99%	0.96%	$85,830	$34,838
Dallas	0.94%	0.94%	$68,949	$52,939

cities. In addition, that highly dense urban cities with high marginal congestion, large damages from emissions and a clean electric grid imply greater environmental and congestion benefits from switching to electric scooters as compared to less dense, less congested cities, with lower emission damages, and a less clean electric grid that draws on power from coal powered plants.

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Table A1: Description of Variables

Mode Variables	Variable Description
Trip Cost	The nominal cost of a trip conditional on the trips distance and time from the origin to the final destination. The cost function,
Trip Time	The estimated time of the trip depends on the distance of the trip and MPH
Mode Temp. Deviation	The deviation of the temperature in the mode environment from 70 degree Fahrenheit.
Individual Variables	**Variable Description**
Age	Reported age from 1-99 years old
Sex	Female=1, Male=0
Education	The number of years of schooling.
Household Size	Total number of members in a family unit that live under in the same house
Family Income	Household salary between \$0 - \$250k
Health	An opinion ranking of the surveyors health ranging from 0 to 100, where 100 is great health.
Temperature Deviation	The temperature deviation of the weather from 70 degree Fahrenheit.
Travelers	The number of companions accompanying the consumer on the trip.

Table A2: MPH speeds (mph) and Parking Costs

	Vehicle Speeds				Metro Speeds	Parking Cost	
City	Median	8:00 AM	12:00 PM	5:00 PM	Average	Monthly	Daily
Atlanta	19.0	21.8	20.6	19.9	11.6	80	2.7
Austin	19.2	21.3	21.2	20.1	7.7	140	4.7
Baltimore	19.9	23.8	22.8	21.1	10.0	193	6.4
Birmingham	22.3	23.1	25.1	22.5	10.5	83	2.8
Boston	17.6	21.8	19.7	19.2	8.7	458	15.3
Buffalo	18.2	23.1	18.6	21.2	7.9	102	3.4
Charlotte	20.6	23.0	21.6	22.1	13.1	95	3.2
Chicago	17.0	20.0	19.5	20.1	9.8	309	10.3
Cincinnati	19.9	26.7	21.1	20.2	4.8	65	2.2
Cleveland	18.6	24.5	19.5	22.6	9.5	115	3.8
Columbus	19.9	22.2	22.9	20.7	10.7	83	2.8
Dallas	18.9	22.5	20.3	21.0	10.5	75	2.5
Denver	18.1	18.1	20.2	20.8	12.4	170	5.7
Detroit	20.5	22.9	19.1	23.6	7.3	145	4.8
Grand Rapids	22.1	27.2	21.9	21.5	10.3	128	4.3
Hartford	19.8	23.4	18.7	23.4	4.9	110	3.7
Houston	18.3	21.6	20.0	20.2	9.5	218	7.3
Indianapolis	19.2	19.1	25.3	22.2	17.5	133	4.4
Jacksonville	19.3	20.6	18.5	21.5	5.4	78	2.6
Kansas City	18.5	24.3	21.9	21.7	7.1	50	1.7
Las Vegas	17.3	20.2	20.2	18.2	6.3	58	1.9
Los Angeles	15.5	18.2	18.3	16.8	9.5	125	4.2
Louisville	22.3	25.4	22.3	26.1	10.8	65	2.2
Memphis	22.0	27.0	23.3	26.7	6.3	70	2.3
Miami	15.0	20.0	17.7	17.0	11.5	98	3.3
Milwaukee	19.5	22.7	20.7	21.7	8.0	118	3.9
Minneapolis	23.6	25.8	25.1	26.4	14.3	168	5.6
Nashville	21.0	22.5	19.3	21.9	13.5	128	4.3
New Orleans	15.3	24.6	16.8	20.8	7.0	173	5.8
New York	17.9	21.9	18.5	20.6	9.8	732	24.4
Oklahoma City	20.5	21.5	18.9	25.6	7.4	25	0.8
Orlando	18.1	23.2	16.3	19.2	16.2	90	3.0
Philadelphia	18.3	20.9	19.1	20.0	7.4	325	10.8
Phoenix	19.4	22.1	20.2	23.3	9.2	65	2.2
Pittsburgh	16.6	17.1	19.2	17.9	4.3	245	8.2
Portland	17.8	19.9	19.3	18.1	8.8	197	6.6
Providence	18.3	22.2	24.8	20.4	4.4	53	1.8
Raleigh	21.2	23.1	22.6	20.6	10.4	68	2.3
Richmond	22.4	24.1	16.3	24.2	4.2	186	6.2
Riverside	18.3	20.9	19.1	20.7	9.3	157	5.2
Rochester	22.1	24.5	21.8	23.7	4.8	66	2.2
Sacramento	18.2	21.4	19.7	19.9	12.5	180	6.0
St. Louis	20.4	25.6	22.5	24.6	15.3	93	3.1
Salt Lake City	17.8	21.1	20.0	20.3	11.2	151	5.0
San Antonio	19.4	22.6	21.0	20.4	9.0	85	2.8
San Diego	18.3	21.3	20.1	20.0	8.1	185	6.2
San Francisco	15.5	18.5	18.2	17.5	11.7	320	10.7
San Jose	15.8	18.1	18.9	18.2	12.0	108	3.6
Seattle	17.4	18.8	20.2	17.7	13.1	288	9.6
Tampa	17.2	20.7	17.8	19.2	11.3	51	1.7
Virginia Beach	19.9	22.8	23.4	21.8	32.9	105	3.5
Washington	16.6	19.9	19.1	18.2	7.8	429	14.3

Table A3: Environmental Benefit

	Share Scooter	Reduction Car Share	Enviromental Savings	Enviromental Cost	Enviromental Benefit
Los Angeles	1.54%	1.00%	$699,233	$6,143	$693,089
New York	1.93%	1.06%	$446,145	$21,201	$424,944
Chicago	1.40%	0.92%	$247,416	$4,489	$242,927
Washington	1.76%	1.07%	$135,187	$6,203	$128,984
San Francisco	1.69%	1.05%	$115,932	$2,237	$113,695
Philadelphia	1.26%	0.84%	$108,923	$5,063	$103,860
Miami	0.98%	0.72%	$105,254	$2,876	$102,378
Boston	1.71%	1.06%	$70,596	$6,134	$64,462
Seattle	1.39%	0.92%	$56,904	$1,565	$55,338
Houston	1.10%	0.78%	$54,886	$6,699	$48,187
Dallas	0.94%	0.70%	$53,216	$6,480	$46,737
San Diego	1.01%	0.75%	$46,998	$915	$46,083
Atlanta	0.87%	0.67%	$44,560	$4,430	$40,130
Riverside	1.00%	0.71%	$38,638	$969	$37,669
Denver	0.96%	0.73%	$38,429	$1,288	$37,141
Pittsburgh	0.99%	0.76%	$35,554	$2,414	$33,140
Minneapolis	0.70%	0.52%	$31,831	$685	$31,147
Portland	1.15%	0.84%	$28,511	$1,113	$27,398
Phoenix	0.77%	0.58%	$26,365	$879	$25,485
Tampa	0.79%	0.60%	$24,073	$1,986	$22,087
Charlotte	0.81%	0.61%	$23,587	$1,839	$21,748
Indianapolis	0.85%	0.64%	$21,794	$727	$21,066
Austin	0.93%	0.69%	$20,484	$1,012	$19,473
San Jose	1.18%	0.86%	$19,570	$757	$18,813
Milwaukee	0.90%	0.68%	$19,047	$502	$18,545
Kansas City	0.85%	0.63%	$18,997	$646	$18,351
Nashville	0.72%	0.56%	$19,057	$2,203	$16,854
Detroit	0.89%	0.65%	$18,098	$1,265	$16,833
Sacramento	0.97%	0.73%	$17,540	$707	$16,833
Orlando	0.77%	0.58%	$17,526	$1,254	$16,272
Salt Lake City	0.99%	0.71%	$16,517	$385	$16,131
St. Louis	0.73%	0.55%	$15,826	$629	$15,197
Grand Rapids	0.80%	0.58%	$16,479	$1,835	$14,644
San Antonio	0.70%	0.53%	$14,784	$523	$14,261
Providence	0.87%	0.64%	$15,298	$1,459	$13,839
Las Vegas	0.80%	0.61%	$11,023	$414	$10,609
Raleigh	0.83%	0.61%	$10,788	$393	$10,395
Baltimore	0.80%	0.58%	$11,241	$924	$10,317
Memphis	0.91%	0.67%	$11,004	$1,072	$9,932
Cleveland	0.88%	0.65%	$10,381	$692	$9,689
Buffalo	0.87%	0.65%	$9,410	$324	$9,086
Cincinnati	0.71%	0.59%	$9,227	$300	$8,927
New Orleans	1.03%	0.72%	$9,606	$967	$8,639
Richmond	0.73%	0.56%	$9,340	$1,044	$8,295
Virginia Beach	0.73%	0.55%	$9,123	$1,125	$7,999
Rochester	0.73%	0.56%	$8,237	$934	$7,303
Jacksonville	0.74%	0.57%	$7,546	$304	$7,242
Oklahoma City	0.89%	0.66%	$7,508	$316	$7,193
Louisville	0.68%	0.49%	$5,829	$142	$5,686
Columbus	0.83%	0.61%	$6,009	$603	$5,406
Hartford	0.75%	0.57%	$2,949	$249	$2,700
Birmingham	0.60%	0.48%	$2,165	$262	$1,903

Total $2,824,642

Table A4: Annual Congestion Hours Per Driver Per MSA

	Congestion (annual hrs.)	Drivers (thous)	Δ Congestion (2016-2017)	Δ Drivers (2016-2017)	Marginal Congestion
Los Angeles	119	5,905	3	6	0.48
Washington	102	1,888	3	20	0.20
New York	92	6,003	2	9	0.29
San Jose	81	1,024	1	4	0.35
Boston	80	1,736	3	15	0.25
Seattle	78	1,543	2	17	0.14
Houston	75	2,498	2	31	0.05
Chicago	73	3,450	1	3	0.00
Riverside	70	1,114	2	14	0.24
Miami	69	2,808	2	22	0.15
Dallas	67	2,645	2	30	0.09
Austin	66	785	3	20	0.08
Portland	66	900	2	13	0.12
San Diego	64	1,452	0	17	0.14
Philadelphia	62	2,308	2	0	0.67
Phoenix	62	2,039	1	11	0.12
Denver	61	1,340	2	9	0.16
Detroit	61	2,072	0	0	0.06
Baltimore	59	1,280	2	5	0.26
Sacramento	59	930	2	6	0.17
Nashville	58	626	1	3	0.28
New Orleans	58	518	1	5	0.30
Charlotte	57	673	3	22	0.08
Orlando	57	839	2	16	0.12
Minneapolis	56	1,402	2	6	0.21
Cincinnati	52	853	1	7	0.15
Las Vegas	51	1,025	1	16	0.09
San Antonio	51	1,025	1	15	0.12
Columbus	50	760	2	4	0.13
Hartford	50	447	1	0	0.55
Oklahoma City	50	558	1	4	0.49
Tampa	50	1,325	2	20	0.09
Buffalo	48	449	0	-1	0.00
Indianapolis	48	802	1	4	0.20
Memphis	48	575	1	0	0.46
Providence	48	611	1	3	0.52
Kansas City	47	834	0	0	0.16
Cleveland	46	872	0	0	0.00
Jacksonville	46	593	0	15	0.10
Louisville	46	587	2	2	0.10
Milwaukee	46	689	2	0	0.24
Pittsburgh	46	852	0	0	1.05
St. Louis	46	1,120	0	0	0.00
Virginia Beach	46	748	0	0	0.00
Salt Lake City	45	537	0	2	0.13
Raleigh	42	521	1	13	0.14
Grand Rapids	41	333	0	0	0.14
Birmingham	40	420	1	0	0.20
Rochester	40	359	0	1	0.56
Richmond	35	512	2	3	0.67

Table A5: Congestion Benefit by City

	Share Scooter	Reduction Car Share	Drivers (thous.)	Reduction Car (thous.)	Marginal Congestion	Congestion Reduction	Congestion Benefit (thous)
Los Angeles	1.54%	1.00%	5,905	58.93	0.48	28.05	$2,520,809
New York	1.93%	1.06%	5,190	55.20	0.28	15.46	$1,219,867
Chicago	1.40%	0.92%	3,450	31.68	0.48	15.10	$793,446
Philadelphia	1.26%	0.84%	2,308	19.31	0.67	12.87	$452,865
Miami	0.98%	0.72%	2,808	20.10	0.15	2.92	$125,226
Boston	1.71%	1.06%	1,736	18.40	0.25	4.58	$120,854
Washington	1.76%	1.07%	1,888	20.26	0.20	4.02	$115,281
Atlanta	0.87%	0.67%	2,017	13.47	0.26	3.49	$107,396
Pittsburgh	0.99%	0.76%	852	6.43	1.05	6.74	$87,579
Dallas	0.94%	0.70%	2,645	18.48	0.09	1.72	$69,308
San Jose	1.18%	0.86%	1,024	8.84	0.35	3.09	$48,212
Seattle	1.39%	0.92%	1,543	14.20	0.14	2.03	$47,683
Phoenix	0.77%	0.58%	2,039	11.84	0.12	1.41	$43,892
Houston	1.10%	0.78%	2,498	19.47	0.05	1.04	$39,555
Baltimore	0.80%	0.58%	1,280	7.49	0.26	1.96	$38,285
San Diego	1.01%	0.75%	1,452	10.86	0.14	1.47	$32,469
Minneapolis	0.70%	0.52%	1,402	7.30	0.21	1.50	$32,076
Riverside	1.00%	0.71%	1,114	7.91	0.24	1.87	$31,753
Denver	0.96%	0.73%	1,340	9.74	0.16	1.55	$31,615
Detroit	0.89%	0.65%	2,072	13.46	0.06	0.78	$24,621
Providence	0.87%	0.64%	611	3.89	0.52	2.01	$18,722
Sacramento	0.97%	0.73%	930	6.75	0.17	1.18	$16,715
Memphis	0.91%	0.67%	575	3.83	0.46	1.77	$15,508
Oklahoma City	0.89%	0.66%	558	3.69	0.49	1.81	$15,396
Richmond	0.73%	0.56%	512	2.89	0.67	1.93	$15,065
Tampa	0.79%	0.60%	1,325	7.90	0.09	0.74	$14,984
Indianapolis	0.85%	0.64%	802	5.13	0.20	1.05	$12,823
Portland	1.15%	0.84%	900	7.59	0.12	0.90	$12,364
Milwaukee	0.90%	0.68%	689	4.65	0.24	1.10	$11,575
San Francisco	1.69%	1.05%	792	8.33	0.11	0.89	$10,707
Kansas City	0.85%	0.63%	834	5.26	0.16	0.83	$10,584
San Antonio	0.70%	0.53%	1,025	5.44	0.12	0.64	$9,957
Cincinnati	0.71%	0.59%	853	5.01	0.15	0.76	$9,878
Hartford	0.75%	0.57%	447	2.56	0.55	1.42	$9,699
Nashville	0.72%	0.56%	626	3.51	0.28	0.98	$9,358
New Orleans	1.03%	0.72%	518	3.75	0.30	1.11	$8,788
Las Vegas	0.80%	0.61%	1,025	6.23	0.09	0.55	$8,675
Orlando	0.77%	0.58%	839	4.84	0.12	0.59	$7,560
Columbus	0.83%	0.61%	760	4.62	0.13	0.61	$7,096
Rochester	0.73%	0.56%	359	2.00	0.56	1.11	$6,108
Austin	0.93%	0.69%	785	5.39	0.08	0.43	$5,167
Salt Lake City	0.99%	0.71%	537	3.83	0.13	0.49	$3,976
Raleigh	0.83%	0.61%	521	3.19	0.14	0.46	$3,672
Charlotte	0.81%	0.61%	673	4.08	0.08	0.33	$3,410
Jacksonville	0.74%	0.57%	593	3.37	0.10	0.33	$2,958
Birmingham	0.60%	0.48%	420	2.01	0.20	0.40	$2,578
Louisville	0.68%	0.49%	587	2.87	0.10	0.27	$2,462
Grand Rapids	0.80%	0.58%	333	1.93	0.14	0.28	$1,419
Buffalo	0.87%	0.65%	449	2.94	0.00	0.00	$0
Cleveland	0.88%	0.65%	872	5.71	0.00	0.00	$0
St. Louis	0.73%	0.55%	1,120	6.16	0.00	0.00	$0
Virginia Beach	0.73%	0.55%	748	4.11	0.00	0.00	$0

Total $6,239,997

Figure 7: Annual Congestion Per Driver and Total Vehicle Commuters (thousands)