# Where No Cars Go:
# Free-Floating Carshare and Inequality of Access

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**Abstract**

**Carsharing programs have demonstrated a potential to significantly shift incentives with regard to private vehicle ownership. The advent of free-floating vehicle fleets has enabled providers to offer ubiquitous vehicle access in designated urban areas. The ability of users to choose where to drop off vehicles presents the possibility that the density of available vehicles in particular areas will be insufficient to supply a reasonable level of service to local residents. The current paper will use exclusive data on vehicle location from a free-floating carshare service that operates in ten US cities. Analysis will relate the availability of vehicles to census tract demographics. Results show vehicles cluster in tracts that are disproportionately populated by residents who are educated, young, employed and white. Carshare systems have received significant in kind incentives from government to operate. The mobility benefits of free-floating carshare systems appear to accrue disproportionately to advantaged populations.**

Keywords: Carsharing; Mobility; Equity; Mode Choice; Sharing Economy

# 1 Introduction

Carsharing programs have provided a new way for residents to navigate cities. The increasing popularity of carsharing has proceeded contemporaneously with increased interest amongst city governments regarding the consequences and potential mobility benefits that such systems may bring. Free-floating carshare (FFCS) –those systems which allow users to end trips within a designated urban area, rather than being limited to specific reserved parking stalls– have expanded considerably in US cities. The largest FFCS provider in the US in terms of membership, ridership, and vehicle stock is Car2Go, a service operated by Daimler.

Carsharing services are disproportionately located in more affluent cities. Among US Census defined metropolitan areas, having a Car2Go system correlates with an increase in median household income of $23,000, an increase in average home value of $154,100, and an increase in the share of the adult population with a college degree of 13 percentage points (2011 American Community Survey). Furthermore, the operating areas of Car2Go systems within selected cities are limited to particular areas, chosen by the system operator. This paper will go beyond the recognition that private carshare services may preferentially locate in more affluent areas. This paper will instead consider the distribution of FFCS vehicles *within* their permitted zones, and subsequently look for evidence that vehicles cluster in census tracts of particular demographic composition.

The mobility benefit FFCS brings to residents is related to the availability of FFCS vehicles. If users intend to begin trips proximal to their home, and if vehicles do not appear regularly in that location, the utility of the system is limited for local residents as trips cannot dependably originate from their location. Prior research has provided little evidence concerning whether mobility benefits of FFCS are spread equitably. Consideration of equity is warranted given the significant amount of public subsidy allotted to carsharing systems. In kind subsidies such as free and discounted parking privileges diminish public funds through expenditure or forfeiture of potential revenue (Firnkorn and Müller, 2012; Shaheen et al., 2004). Carshare subsidies are only economically defensible if the costs are exceeded by the public benefit of expanded carshare use.

The CEO of Car2Go recently asserted: "Car2Go is notably improving mobility in North America's increasingly dense urban cores" (Car2Go, 2016). This study will attempt to describe the spatial dispersion of direct mobility benefits. US cities continue to experience strong racial and economic segregation (De la Roca et al., 2014; Krivo et al., 2013). If FFCS programs are disproportionately popular amongst particular socioeconomic groups, the resulting geographic dispersion of vehicles may diminish access for specific subpopulations. Supposed personal mobility benefits of FFCS such as complementarity with public transit and the ability to forego or delay car ownership may be undercut if carshare cannot be reliably accessed from the home.

## 2 Related Literature

Prior research regarding the social consequences of carsharing has been primarily limited to understanding environmental and autodependency implications. Research has also examined the demographic composition of carshare users for fixed-location carshare services, where fixed-location refers to a system reliant on specific and permanent parking stalls to accommodate shared vehicles. The current paper is concerned with the implications of FFCS in terms of spatial equity in service accessibility, for which there is little previous research. For a general overview of FFCS in North America see Shaheen et al. (2015b), and for an international overview see Shaheen and Cohen (2013).

The potential environmental consequences of FFCS have been well covered in the literature and represent a likely benefit of FFCS that exists independently of equity considerations. Firnkorn and Müller (2011, 2015) used data on Car2Go users to estimate the potential for environmental improvement due to reductions in private vehicle ownership and related reductions in greenhouse gasses. Firnkorn and Müller (2011, 2015) presented strong evidence that environmental progress may be attainable through FFCS. Additional studies of fixed-location carshare have indicated that uptake leads to reductions in private vehicle ownership (Cervero et al., 2007; Firnkorn and Müller, 2012; Martin et al., 2010). Martin and Shaheen (2011) outlined a direct link between carshare uptake and reductions in household greenhouse gas emissions. The potential for reductions in greenhouse gas emissions and local pollutants brought about by expanded carshare adoption is a vitally important issue, and may hold environmental benefits which extend across society.

Contrastingly, carsharing's value in terms of improved urban mobility is not necessarily shared evenly. The mobility benefits of FFCS may accrue asymmetrically across society, particularly if access to the system is uneven across the city.

Cervero et al. (2007) provided a review of San Francisco's roundtrip, fixed-location *City CarShare* program, including information on demographics of program participants. Cervero et al. (2007) reported program members to be on average marginally older and have a higher income than the local population. The study also found 83% of members were white, while the local population was only 50% white.

Costain et al. (2012) investigated user data from a popular carsharing program in Toronto. Although the system studied in Costain et al. (2012) is not a free-floating system, the authors were able to identify neighbourhood level characteristics that correlate with usage of locally parked shared vehicles. The proximity of parked vehicles to a resident's home was found to be a "critical factor" in determining whether a resident would sign up for carshare. The majority of trips were made by members who lived within 1 km of a carshare lot. Costain et al. (2012) argued that carsharing is "providing a segment of the population with enhanced accessibility and mobility" and subsequently cited previous studies suggesting that those benefiting from carshare are predominately low and middle income residents. The current study makes a conflicting finding with regards to the effect of socioeconomic characteristics that relate to carshare use. Costain et al. (2012) noted the unfortunate lack of datasets available to analyse carsharing, an issue the current project works to remedy.

Sioui et al. (2013) examined the demographics of fixed-location carshare users in Montreal. The research showed users of the service skewed younger and were more likely to have a full-time job when compared to the general population. Among members of the service, Sioui et al. (2013) found single adult households to use the carshare service with the highest frequency.

Shaheen et al. (2015a) investigated the appeal of carsharing to the elderly. The study relied on a limited survey of a retirement community. Shaheen et al. (2015a) found moderate interest amongst the elderly for participation in carshare, though the demographic composition of the sample was disproportionately white and highly educated, limiting the applicability of the findings to diverse populations.

Kim (2015) contributed a study with some resemblance to the current paper. Kim (2015) analyzed data from the largest fixed-location carshare service in New York City (*Zipcar*), comparing vehicle availability with neighbourhood demographics. Kim (2015) investigated differential vehicle use for vehicles stationed in neighbourhoods of low socioeconomic status

(SES). Kim (2015) lacked statistical power to make conclusive statements on differential use; however, the study argued that carshare users appear to comprise a diverse population, refuting previous literature that found "young, white, and middle-income persons are the typical users of carshare."

De Lorimier and El-Geneidy (2013) studied usage data and vehicle placement for a fixed-location carshare service in Montreal. The study found carshare vehicles were used more often when additional carshare vehicles were clustered nearby, suggesting that carshare uptake is higher when users experience higher odds of local vehicle availability, this hypothesis is also supported by Costain et al. (2012). The current paper assumes local FFCS service dependability is related to the frequency of locally available vehicles. Understanding which segments of society are reaping mobility benefits from carshare is important to forming an understanding of the equity implications of expanded carshare use. This study will compliment prior research regarding how local demographics interact with carshare.

## 3 Data

This study uses an original data set of observed Car2Go vehicle locations. The data was obtained by regularly querying the Car2Go Application Programming Interface (API) through an external server. The

API provides the current location of every available Car2Go vehicle in the United States. The API was queried approximately every 18 minutes for a six month period from September 1, 2015 to February 29, 2016; creating ordered snapshots of vehicle locations. Observations occurring between midnight and 5 am local time are dropped, as this time period exhibits very little variation and is unlikely to be relevant to most users. The resulting data set contains 44,014,696 observations of available vehicles. These data provide a rich description of where Car2Go vehicles are frequently found within their city, and represents the most extensive data set on FFCS vehicle location in the extant literature. During the period of study Car2Go operated in ten US cities, which are identified in Table 1. Data from all ten cities are utilized. Car2Go service began in Arlington, Virginia shortly after the start of this study and as a result Arlington is not represented in the data.

The API provides precise latitude and longitude coordinates. To accommodate analysis at the census tract level, the latitude and longitude coordinates are matched to coded US census tracts using the US Federal Communications Commission's (FCC) Census Block Conversion API.

Demographic information at the census tract level is taken from the 2013 American Community Survey (ACS), 5-year estimates. The 5-year estimates are derived from survey responses recorded from 2009 through 2013 and are based on responses from approximately 5% of the US population. The US Census also provides data on the geographic characteristics of census tracts, including area.

In order to compare the level of service provided by the FFCS to census tracts, instances where the tract has at least one available vehicle are flagged. Subsequently, the number of flagged queries is divided by the total number of queries, producing the percentage of time there was at least one vehicle available in the tract across the period of study. This census tract level metric is calculated separately for each month and the average is taken across months in order to ensure each month is given equal weight.

Car2Go delineates a "home zone" within which users can drop off vehicles at the conclusion of a trip. Across the 10 cities, 1,830 census tracts were within a "home zone" and contained an available vehicle at some point during the data recording period. Of these tracts, 1,728 possessed a full set of ACS variables and were retained for analysis. Figure 1 provides maps displaying the location of retained census tracts for each city. On average, the home zone contains 63% of the primary city's population and 16% of the metropolitan population. Figure 1 also shows the ratio of income and home prices inside the home zone relative to that inside the primary city and inside the metropolitan area. Home prices are typically higher within the home zone than the greater metropolitan area, while incomes are typically lower. Table 1 displays the average share of time a tract had a vehicle available across cities, as well as the average density of available vehicles across all observed tracts. Table 2 displays summary statistics for all tract level variables used in analysis. The demographic variables examined are correlated to varying extents. Table 3 provides correlations between all census tract demographic variables and metrics for vehicle availability.

# 4 Methodology

Analysis will use an OLS regression approach to identify which census tract types enjoy a high level of access to FFCS vehicles. Although trips may originate from locations away from the user's home, measuring trips originating from the home captures the level of local vehicle availability and can serve as a proxy for the level of service experienced by local residents. The pertinence of estimating spatial demographic variation in vehicle access is predicated on the assumption that FFCS service is improved when trips can reliably originate from a user's home.

The statistical analysis will take two primary measures to improve the precision and interpretation of estimates. First, metro fixed effects will be used. Metro fixed effects allow estimates to correspond to the impact of demographic differences between census tracts but within a particular metro, rather than assuming tracts are comparable between metros. This correction is necessary because the average density of FFCS vehicles varies substantially between metros (as shown in Table 1), as does demographic composition. Second, census tract population density and land area are controlled for. Tract population density and land area have a mechanical relationship with local vehicle demand and availability as well as a strong relationship with demographics. The omission of these controls would cause estimates to be difficult to disentangle from the impact of population density and variable tract size.

The general model being estimated is as follows:

$$V_i = \beta_0 + \beta_1\gamma_i + \beta_2 D_i + \beta_3 A_i + \phi M_i + \epsilon_i \tag{1}$$

Where $V$ is the portion of time at least one vehicle is locally available, $\gamma$ is a demographic characteristic of interest, $D$ is the population density, $A$ is the census tract area in km$^2$, $M$ is a metropolitan area fixed effect, and $i$ indexes census tract.

This model allows estimated effects to be interpretable as the partial effect of census tract demographic composition within a city, above and beyond the confounding effect of tract density and geographic size. This paper does not attempt to establish a causal mechanism that explains *why* vehicles cluster in tracts of particular demographics. Rather, this paper attempts to report how vehicle availability varies with local demographic characteristics. A notable limitation of this approach is an inability to disentangle the effect of averaged tract characteristics from differences arising as a result of individual demographic characteristics. Accessing disaggregated user data would provide invaluable insights if they could be obtained. In relation to the providers of carshare, the reported effects do not necessarily represent active intervention by the provider. Rather, the disparity is a market outcome driven by user behaviour.

# 5 Results

Table 4 reports the estimation results of Equation 1. Regressions include control variables for tract population density and land area as well as metro fixed effects. Standard errors are clustered at the metro level. Each column of Table 4 estimates the partial effect of a separate demographic variable, indicated at the top of each column.

This study finds local education level to be an important characteristic in determining FFCS vehicle availability. High school and college completion rates have a significant and positive relationship with FFCS vehicle availability. A 10 percentage point increase in a tract's high school completion rate increases the probability of a vehicle being available locally by 4.1 percentage points. A similar increase in the college completion rate increases the probability by 3.9 percentage points.

Racial demographics are important predictors of vehicle availability. A 10 percentage point increase in the white population share significantly increases the likelihood of vehicle availability by 1.6 percentage points, while a similar increase in the black population share lowers the probability by 1.3 percentage points. The effect of white population share echoes the finding of Cervero et al. (2007), which found white residents were overrepresented in San Francisco's *City CarShare* system. The Hispanic and Asian population shares were tested as well (not shown). Hispanic composition had no statistically significant effect while the effect of Asian population share was a decrease in the likelihood of vehicle availability of 1.2 percentage points, significant at the 5% level.

The labour market outcomes of local residents are strongly predictive of vehicle availability. A 10 percentage point increase in the unemployment rate corresponds to a 6.9 percentage point reduction in the availability measure, while a 10 percentage point increase in the rate of labour force participation corresponds to a 6.7 percentage point increase in likelihood of availability. This finding matches that of Sioui et al. (2013) that found higher use of fixed-location carshare amongst employed residents.

Previous studies have found carsharing to be disproportionately popular amongst young adults (Firnkorn and Müller, 2012; Sioui et al., 2013). This study supports that finding in the context of FFCS. The portion of a tract's population that is between the ages of 20 and 34 is a powerful and consistent predictor of vehicle availability. A 10 percentage point increase in the share of 20-34 year old residents corresponds to a 7.7 percentage point increase in the likelihood a vehicle will be available. The share of residents over the age of 65 has a negative but only marginally statistically significant effect on vehicle availability.

The state of a tract's real estate market is somewhat predictive of vehicle availability. A $100,000 increase in median local home value increases vehicle availability by 3.3 percentage points.

Interestingly, median household income does not have a significant effect on vehicle availability. Although the direction of the estimated coefficient is consistent with high SES areas having higher vehicle availability, income has no statistically significant relationship with local FFCS vehicle availability. This finding is loosely consistent with Firnkorn and Müller (2012) that found Car2Go members in Ulm, Germany were representative of the general population in terms of income. Weak income effects indicate it is not that vehicles are clustering in "rich" areas, which could be explained simply by the higher consumption of goods and services generally amongst richer residents. Results instead point to differences in availability driven by local differences in education, race, labour market conditions, age profile, and real estate conditions.

A methodological concern may be that carshare use is clustered in the CBD and tracts within the CBD have particular demographic characteristics. Table 4 regressions are repeated with the inclusion of a tract level control variable for employment density, measured in jobs/km$^2$ (not shown). Job location data is obtained from the US Census, 2014 Longitudinal Employer-Household Dynamics data set. The inclusion of the job density variable generates no statistically significant changes in the 10 demographic effects reported in Table 4, suggesting the demographic effects are not simply proxies for CBD proximity, but that demographics are meaningful predictors of vehicle availability.

From the perspective of a user, the dependability of FFCS is related to the possibility that there will be no locally available vehicles, which would prevent the trip from taking place through FFCS. This important case supports the choice to use the likelihood of locally available vehicles as the dependant variable. An alternative measure of vehicle availability is the average density of vehicles within the census tract. Table 5 repeats the methodology of Table 4, but replaces the dependent variable with the average number of available vehicles in the census tract, divided by tract area in $km^2$. In general, the statistical significance of results are very similar between the two dependant variables, suggesting results are robust to the choice of vehicle availability measure. The share of the tract's population between 20 and 34 years of age has the most significant effect on average vehicle density: every 12 percentage point increase in this population share garners an additional locally available vehicle, on average.

The OLS analysis makes the strong assumption that demographic effects are linear with respect to the measures of vehicle availability. This methodology provides reasonable aggregate estimates that accurately capture the overall discrepancy in access brought about by differences in demographics; however, aggregate estimates may disguise aspects of relationships that operate differentially over discrete ranges. Figure 2 shows the demographic characteristics graphed against vehicle availability, using a fractional polynomial graphing procedure. This strategy reveals how predicted vehicle availability changes with respect to observed demographics, across the range of possible demographic values. Dotted lines are included representing the estimated linear relationship. Consistent with Table 4, Figure 2 removes the partial effects of tract density, land area and metro fixed effects and displays demographic impacts "above and beyond" these controls.

Figure 2 reveals that the linear assumption is consistent with many of the observed relationships in the data. The somewhat non linear effect of college education and median home value suggest that these variables may increase vehicle availability up to a point, beyond which additional increases have little effect. Nonlinearities highlight which portions of the demographic distributions drive partial effects. For example, the effect of white and black population share appear to be driven by tracts with very few white residents or with a majority of black residents. This suggests a threshold effect where vehicles are conspicuously absent from tracts with few white residents.

The reported effects vary somewhat across the ten cities that comprise the sample. Table 6 provides estimates for the likelihood of vehicle availability, but breaks the sample into separate estimates for each metro. Similar to Table 4 and 5, controls for tract population density and land area are included in regressions. To conserve space, Table 6 displays only the coefficient of interest ($\beta_1$), suppressing the partial effects of controls. The most persistently predictive demographic measure is the share of 20-34 year old residents and the college completion rate which positively predict vehicle availability in all ten cities.

# 6 Conclusion

The rapid expansion of FFCS in the US has been aided by enthusiasm from cities that hope to support environmental and mobility goals. Carsharing has been shown in prior studies to lead to reductions in vehicle ownership and hold corresponding environmental benefits. This paper has presented evidence of a disparity in vehicle accessibility along spatial demographic lines.

FFCS has the curious property that service dependability is dictated in part by the choices of other users. If other users do not regularly park vehicles near a user's normal trip origin, the usability of the system is diminished. Observed vehicle availability reveals that cars are not uniformly distributed within their "home zone," but cluster in areas of particular demographic characteristics. Results show service dependability is higher in tracts that are disproportionately populated by residents who are educated, young, employed and white.

A full understanding of the determinates of carshare usage and vehicle distribution must consider the myriad interactions between neighbourhood infrastructure, demographics, and mobility preferences, which vary across cities. Dowling and Kent (2015) articulates the role of "residential and commercial densities, active transport networks and constrained on-street parking," which affect carshare uptake. Shaheen et al. (2004) as well as Huwer (2004) find that the availability of local transportation alternatives are important to the local adoption of carshare. The interaction of transit, carshare, and demographics is worthy of further research.

Shaheen et al. (2004) previously argued that low SES residents have displayed limited participation in carshare, though Shaheen et al. (2004) cited a lack of available data sets to fully test this hypothesis. The current paper contributes to overcoming this barrier by providing a description of tract level characteristics that correlate with FFCS vehicle access. Collection of microdata at the user level is needed to further clarify the relationship between demographics and FFCS access and use. Government has a significant role in negotiating the implementation of carshare and in setting relevant public policy. If public funds continue to be directed towards the promotion of FFCS, insistence by government that FFCS providers ensure service for marginalized communities could be a warranted direction for future policy.

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**Table 1:** City Characteristics

| City | Available Vehicle Likelihood | Available Vehicles / $km^2$ | CBSA Population | # of Tracts Observed | Available Fleet Size |
|---|---|---|---|---|---|
| Austin, TX | .67 | 1.96 | 1,690,166 | 80 | 338 |
| Columbus, OH | .58 | 1.91 | 1,654,199 | 68 | 195 |
| Denver, CO | .59 | 2.19 | 2,445,687 | 102 | 330 |
| Miami, FL | .60 | 3.77 | 5,582,351 | 120 | 248 |
| Minneapolis, MN | .60 | 1.64 | 3,153,288 | 249 | 512 |
| New York City, NY | .38 | 3.21 | 19,533,586 | 588 | 466 |
| Portland, OR | .61 | 2.49 | 2,172,972 | 117 | 455 |
| San Diego, CA | .71 | 3.08 | 3,105,989 | 87 | 367 |
| Seattle, WA | .74 | 2.49 | 3,449,059 | 147 | 671 |
| Washington, DC | .70 | 4.76 | 5,389,996 | 170 | 653 |

Vehicle likelihood and vehicle density variables are the average values across all observed tracts within each CBSA. Available vehicle likelihood corresponds to $V$ in equation 1. Available fleet size is calculated as the number of unique vehicles observed in the city, averaged across the days of observation.

**Table 2:** Census Tract Summary Statistics

| **Variable** | **Mean** | **Std. Dev.** |
|---|---|---|
| Vehicle availability likelihood | 0.555 | 0.323 |
| Vehicles per $km^2$ | 2.892 | 2.669 |
| Population density ($pop/km^2$) | 9,451 | 9,808 |
| High school completion rate | 0.843 | 0.130 |
| College completion rate | 0.404 | 0.216 |
| White population share | 0.623 | 0.276 |
| Black population share | 0.189 | 0.27 |
| Median household income ($) | 54,919 | 25,220 |
| Labour force participation rate | 0.682 | 0.099 |
| Unemployment rate | 0.101 | 0.062 |
| Median home value ($) | 410,094 | 213,133 |
| Age 20-34 population share | 0.289 | 0.115 |
| Age > 65 population share | 0.112 | 0.057 |
| N | 1728 | |

**Table 3:** Correlation Table

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Vehicle availability likelihood | 1.000 | | | | | | | | | | | |
| (2) Vehicles per km$^2$ | 0.505 | 1.000 | | | | | | | | | | |
| (3) Population density | -0.313 | 0.204 | 1.000 | | | | | | | | | |
| (4) High school completion rate | 0.280 | 0.057 | -0.389 | 1.000 | | | | | | | | |
| (5) College completion rate | 0.353 | 0.188 | -0.247 | 0.792 | 1.000 | | | | | | | |
| (6) White population share | 0.168 | 0.022 | -0.289 | 0.490 | 0.566 | 1.000 | | | | | | |
| (7) Black population share | -0.070 | -0.017 | 0.103 | -0.202 | -0.401 | -0.840 | 1.000 | | | | | |
| (8) Median household income | 0.089 | 0.006 | -0.176 | 0.577 | 0.729 | 0.396 | -0.296 | 1.000 | | | | |
| (9) Labour force participation rate | 0.308 | 0.153 | -0.211 | 0.468 | 0.558 | 0.326 | -0.252 | 0.434 | 1.000 | | | |
| (10) Unemployment rate | -0.132 | -0.088 | 0.043 | -0.418 | -0.562 | -0.580 | 0.581 | -0.504 | -0.385 | 1.000 | | |
| (11) Median home value | -0.093 | 0.200 | 0.476 | 0.052 | 0.266 | 0.051 | -0.133 | 0.409 | -0.036 | -0.244 | 1.000 | |
| (12) Age 20-34 population share | 0.315 | 0.344 | -0.011 | 0.190 | 0.316 | 0.152 | -0.153 | -0.113 | 0.443 | -0.174 | -0.055 | 1.000 |
| (13) Age > 65 population share | -0.120 | -0.069 | -0.033 | 0.073 | 0.013 | 0.110 | -0.051 | 0.106 | -0.403 | -0.073 | 0.105 | -0.471 |

**Table 4:** Effect of Census Tract Characteristics on Probability of a Locally Available Vehicle

| | [High School Comple- tion Rate] | [College Comple- tion Rate] | [White Pop. Share] | [Black Pop. Share] | [Unemployment Rate] | [Labour Force Partic. Rate] | [Age 20-34 Pop. Share] | [Age > 65 Pop. Share] | [Median Home Value ($1,000,000)] | [Median Household Income ($1,000)] |
|---|---|---|---|---|---|---|---|---|---|---|
| [Demographic Covariate] | .407** | .387*** | .157*** | -.128*** | -.686*** | .673*** | .774*** | -.577* | .325*** | .046 |
| | (.203) | (.083) | (.054) | (.048) | (.236) | (.122) | (.130) | (.297) | (.120) | (.070) |
| Pop Density | -.0006 | -.001 | -.001 | -.002 | -.002 | -.003*** | -.004*** | -.003*** | -.001 | -.002 |
| | (.002) | (.001) | (.001) | (.001) | (.001) | (.0009) | (.001) | (.0009) | (.002) | (.001) |
| Land Area | -.013*** | -.012*** | -.013*** | -.013*** | -.013*** | -.012*** | -.010*** | -.012*** | -.013*** | -.013*** |
| | (.004) | (.004) | (.004) | (.004) | (.004) | (.004) | (.003) | (.004) | (.004) | (.004) |
| Const. | .360** | .526*** | .587*** | .718*** | .763*** | .210** | .418*** | .755*** | .625*** | .686*** |
| | (.178) | (.044) | (.045) | (.012) | (.019) | (.096) | (.051) | (.026) | (.035) | (.035) |
| City Fixed Effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 |
| $R^2$ | .220 | .258 | .213 | .208 | .216 | .236 | .266 | .209 | .221 | .200 |

Significance levels: $*$ : 10% $**$ : 5%. $***$ : 1%. Robust standard errors in parenthesis. The partial effect of a separate demographic covariate on vehicle availability is estimated in each column.

**Table 5:** Effect of Census Tract Characteristics on Density of Locally Available Vehicles (vehicles/km$^2$)

| | [High School Completion Rate] | [College Completion Rate] | [White Pop. Share] | [Black Pop. Share] | [Unemployment Rate] | [Labour Force Partic. Rate] | [Age 20-34 Pop. Share] | [Age > 65 Pop. Share] | [Median Home Value ($1,000,000)] | [Median Household Income ($1,000)] |
|---|---|---|---|---|---|---|---|---|---|---|
| [Demographic Covariate] | 3.778** | 3.252*** | 2.040*** | -2.081** | -6.983*** | 6.439*** | 8.634*** | -4.648*** | 2.268* | .418 |
| | (1.619) | (.721) | (.745) | (.930) | (2.702) | (1.607) | (1.056) | (1.074) | (1.196) | (.911) |
| Pop Density | .080 | .072 | .077 | .073 | .068 | .059 | .042 | .059 | .072 | .070 |
| | (.055) | (.047) | (.049) | (.048) | (.049) | (.044) | (.028) | (.049) | (.054) | (.054) |
| Land Area | -.083** | -.078** | -.083** | -.083** | -.085** | -.073** | -.050** | -.079** | -.084** | -.084** |
| | (.038) | (.036) | (.037) | (.037) | (.039) | (.034) | (.024) | (.036) | (.037) | (.040) |
| Const. | -1.215 | .488 | .447 | 2.177*** | 2.580*** | -2.750** | -1.216*** | 2.396*** | 1.439*** | 1.818*** |
| | (1.501) | (.435) | (.668) | (.119) | (.233) | (1.227) | (.461) | (.161) | (.407) | (.468) |
| City Fixed Effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 | 1728 |
| $R^2$ | .178 | .212 | .184 | .183 | .176 | .200 | .272 | .160 | .167 | .153 |

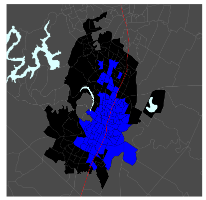
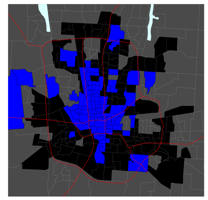
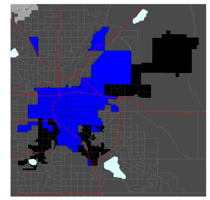
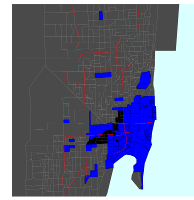
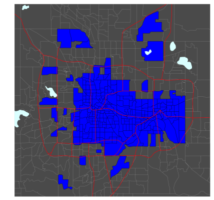
Significance levels: $*$ : 10% $**$ : 5%. $***$ : 1%. Robust standard errors in parenthesis. The partial effect of a separate demographic covariate on vehicle density is estimated in each column.

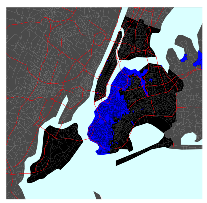
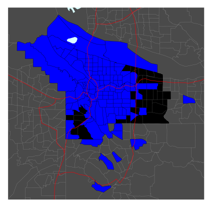
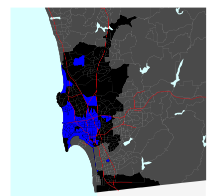
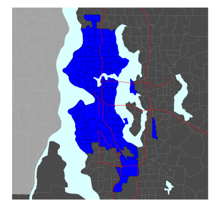
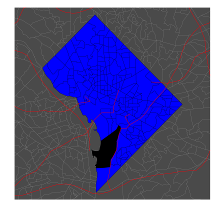
**Table 6:** Effect of Census Tract Characteristics on Probability of a Locally Available Vehicle, by City

| | [High School Completion Rate] | [College Completion Rate] | [White Pop. Share] | [Black Pop. Share] | [Unemployment Rate] | [Labour Force Partic. Rate] | [Age 20-34 Pop. Share] | [Age > 65 Pop. Share] | [Median Home Value ($1,000,000)] | [Median Household Income ($1,000)] |
|---|---|---|---|---|---|---|---|---|---|---|
| Austin | | | | | | | | | | |
| [Demographic Covariate] | .897*** | .763*** | .977*** | -1.381*** | -2.746*** | .878** | 1.119*** | -1.705*** | 1.222*** | .239 |
| | (.320) | (.159) | (.279) | (.463) | (.962) | (.412) | (.395) | (.657) | (.314) | (.179) |
| Columbus | | | | | | | | | | |
| [Demographic Covariate] | 1.722*** | .783*** | .246 | -.302 | -1.281** | .936** | 1.268*** | -1.298 | 2.119*** | .119 |
| | (.421) | (.180) | (.196) | (.199) | (.535) | (.440) | (.234) | (1.015) | (.589) | (.222) |
| Denver | | | | | | | | | | |
| [Demographic Covariate] | .296 | .407** | .388* | -.251 | -.686 | .379 | .896** | .285 | .452* | -.006 |
| | (.309) | (.168) | (.214) | (.258) | (.743) | (.478) | (.355) | (.662) | (.246) | (.135) |
| Miami | | | | | | | | | | |
| [Demographic Covariate] | .597*** | .357** | -.229 | .097 | -.292 | .859*** | 1.025*** | -.787* | .096 | -.043 |
| | (.231) | (.160) | (.146) | (.136) | (.423) | (.294) | (.268) | (.467) | (.187) | (.123) |
| Minneapolis | | | | | | | | | | |
| [Demographic Covariate] | .293* | .333*** | .146* | -.124 | -.323 | .809*** | .937*** | -1.640*** | .198 | -.045 |
| | (.157) | (.087) | (.077) | (.110) | (.279) | (.232) | (.178) | (.428) | (.249) | (.091) |
| NYC | | | | | | | | | | |
| [Demographic Covariate] | -.034 | .102** | .087*** | -.080*** | -.094 | .377*** | .565*** | -.360** | .073 | -.015 |
| | (.060) | (.049) | (.028) | (.025) | (.149) | (.083) | (.093) | (.170) | (.052) | (.044) |
| Portland | | | | | | | | | | |
| [Demographic Covariate] | 1.582*** | .646*** | .311 | .672* | -2.190** | 1.298*** | .819** | -1.367* | .582** | .071 |
| | (.493) | (.194) | (.320) | (.350) | (1.038) | (.415) | (.327) | (.756) | (.282) | (.136) |
| San Diego | | | | | | | | | | |
| [Demographic Covariate] | 1.130*** | .892*** | 1.297*** | .057 | -3.179*** | 1.017*** | .750*** | 1.406** | .492*** | .350* |
| | (.168) | (.212) | (.174) | (.869) | (.622) | (.320) | (.247) | (.556) | (.176) | (.188) |
| Seattle | | | | | | | | | | |
| [Demographic Covariate] | .390* | .447*** | .203** | -.263 | -1.320* | .606*** | .346** | -.711 | .481*** | .127 |
| | (.221) | (.123) | (.094) | (.197) | (.767) | (.226) | (.167) | (.449) | (.131) | (.085) |
| DC | | | | | | | | | | |
| [Demographic Covariate] | 1.092*** | .418*** | .304*** | -.315*** | -1.008*** | .731*** | .639*** | .968** | .583*** | .304*** |
| | (.259) | (.075) | (.070) | (.067) | (.227) | (.198) | (.165) | (.406) | (.109) | (.066) |

Significance levels: $*$ : 10% $**$ : 5%. $***$ : 1%. Robust standard errors in parenthesis. Each cell of table corresponds to a separate regression. All regressions include control variables for census tract land area and population density.

Figure 1. Comparison of FFCS "Home Zones" to Local Municipal and Metropolitan Boundaries

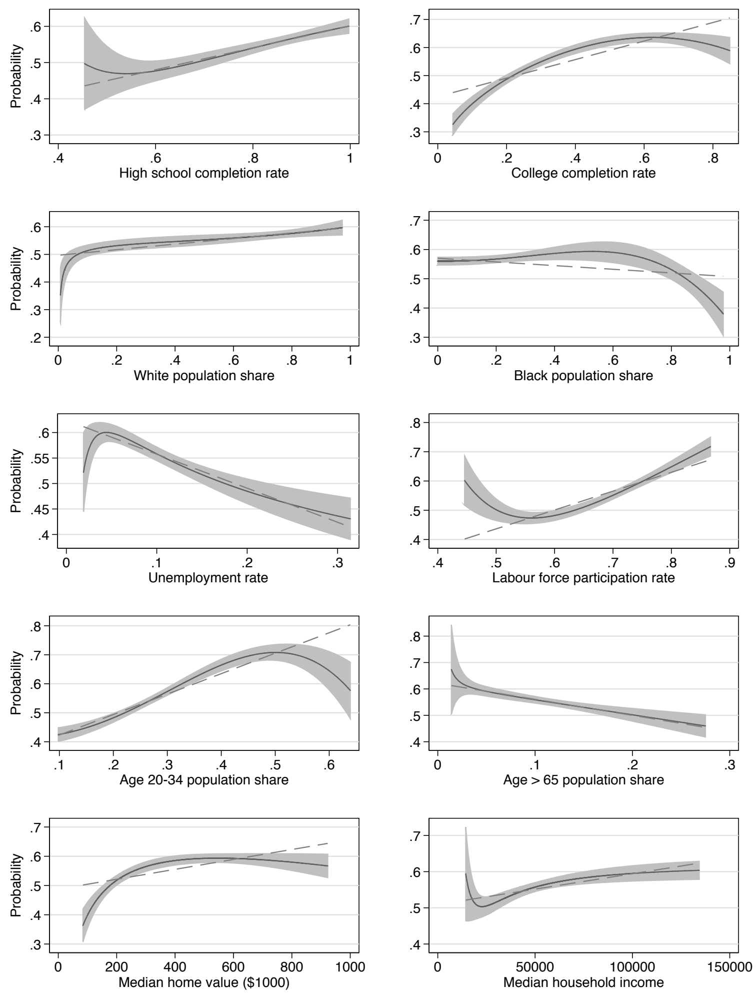
| | **Austin** | | **Columbus** | | **Denver** | | **Miami** | | **Minneapolis** | |
|---|---|---|---|---|---|---|---|---|---|---|
| |  | |  | |  | |  | |  | |
| | CBSA | City | CBSA | City | CBSA | City | CBSA | City | CBSA | City |
| Pop. in home zone | 20% | 42% | 13% | 27% | 17% | 59% | 9% | 73% | 26% | 100% |
| Income ratio | .78 | .88 | .81 | 1.00 | .92 | 1.14 | .89 | 1.42 | .83 | 1.11 |
| Home value ratio | 1.32 | 1.15 | 1.07 | 1.29 | 1.22 | 1.22 | 1.35 | 1.20 | 0.98 | 1.03 |

| | **NYC** | | **Portland** | | **San Diego** | | **Seattle** | | **Washington** | |
|---|---|---|---|---|---|---|---|---|---|---|
| |  | |  | |  | |  | |  | |
| | CBSA | City | CBSA | City | CBSA | City | CBSA | City | CBSA | City |
| Pop. in home zone | 12% | 28% | 20% | 71% | 12% | 29% | 20% | 100% | 11% | 99% |
| Income ratio | .80 | 1.01 | 1.05 | 1.16 | .93 | .92 | 1.03 | 1.06 | .80 | 1.10 |
| Home value ratio | 1.47 | 1.21 | 1.26 | 1.18 | 1.18 | 1.08 | 1.32 | 0.98 | 1.16 | 0.98 |

- Home Zone   - Primary City   - CBSA   - Water   - Interstate Highway

(see caption p.28)

Figure 2: Predicted Likelihood of Having at Least One Locally Available Carshare Vehicle by Demographic Characteristic




(see caption p.28)

(Caption for Figure 1)

A census tract is considered to be part of the home zone if at least one available vehicle was recorded in that tract during the period of study. Population percentages indicate the population share of the indicated geographic unit (CBSA or City) that resides within the home zone. The "city" is the primary city of the CBSA as defined by the US Census Bureau. Income and home value ratios are calculated by dividing the average of the respective tract characteristic within the home zone by the average within the indicated geographic unit (CBSA or City). An income ratio or home value ratio greater than 1 indicates that this characteristic is higher within the home zone than within the comparative geographic unit.

(Caption for Figure 2)

Graphs show predicted likelihood of vehicle availability from indicated demographic characteristics. Solid lines use a fractional polynomial graphing procedure; 90% confidence intervals are shown. Dashed lines assume a linear relationship. Observations are "winsorized" by removing the most extreme 1% of observations from each end of the distribution for each demographic characteristic. Winsorization limits spurious "spikes" at the edges of fitted values that are driven by outliers. Consistent with the empirical approach, the partial effects of population density, land area and differences between metros are controlled for.