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CARSHARING AND THE BUILT ENVIRONMENT:
A GIS-BASED STUDY OF ONE U.S. OPERATOR

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ABSTRACT
The use of carsharing vehicles over a period of 16 months in 2006-07 was compared to built environment and demographic factors in this GIS-based multivariate regression study of an urban U.S. carsharing operator. Carsharing is a relatively new transportation industry in which companies provide members with short-term vehicle access from distributed neighborhood locations. The number of registered carsharing members in North America has doubled every year or two to a current level of approximately 320,000. Researchers have long supposed that public transit access is a key factor driving demand for carsharing. The results of this study, however, find an ambiguous relationship between the activity at carsharing locations and public transit access. Light rail availability is found to have a significant and positive relationship to carsharing demand. Regional rail availability is found to be weakly and negatively associated with carsharing demand, although limitations in the available data make it impossible to ascribe the observed difference to user demand, random variation, or other factors specific to the industry.

INTRODUCTION

Carsharing, a relatively new industry in the United States, has taken root in many urban settings around the country. One question that has been asked since the beginning of the industry, and answered only with partial success, is, "What neighborhood features make for a good carsharing location?" Recent studies have attempted to answer this question using one of two methodologies: surveys of actual users or Geographic Information System (GIS)-based studies of carsharing supply combined with Census data. These methods have consistently found demographic, behavioral, and built environment (BE) factors, such as member age or proximity to transit, to play an important role in carsharing (generally from univariate analyses), although neither method has been able to identify BE factors that interact strongly with demand for carsharing.

This paper uses GIS to model the impact of both Census and specifically collected BE data on carsharing use, as measured by the actual number of user hours each location reports in a typical month. The carsharing usage data are from a single U.S. carsharing operator (CSO), who generously agreed to supply detailed longitudinal data. The participating CSO also requested that their identity remain confidential, and therefore any identifying information has been removed. The data are from a single large metropolitan area.

FROM THE LITERATURE

Defining Carsharing

The term "carsharing" refers to a distinct business process wherein CSOs typically provide their members with short-term vehicle access from a network of unstaffed and distributed neighborhood locations. Members pay a flat hourly and/or per-mile fee that include fuel and insurance costs. These characteristics make carsharing distinct from car rental, where vehicles are rented under a negotiated contract with the customer for longer periods of time, and from centralized, staffed locations. Carsharing comes in many flavors, and to add confusion, the term "carsharing" has also been used to describe both shared-use vehicles and what is now known as ridesharing or carpooling. This paper uses the framework developed by Barth and Shaheen [1] that describes the spectrum of carsharing services from station cars (transit-linked vehicles) to the short-term vehicle use that has become popular worldwide. The rest of this paper will use the term "carsharing" to refer to a "classic" CSO that distributes cars from neighborhood locations on a very short term basis, typically a few hours at a time. In addition, the paper will use the industry term, "pod," to refer to a carsharing parking location that can house one or more vehicles at the same time.

Carsharing Background

Carsharing has been popular in Europe for decades but has only taken a firm hold in North American cities in the last dozen years [2]. In Europe, Sefage, which is the earliest known carsharing organization, circa 1940, provided a way for people who could not otherwise own a car to access one [3]. Now far from its humble origins, carsharing in much of North America and Europe has evolved into a profitable business with appeal to drivers of choice as well as necessity; Zipcar, which is the largest North American carsharing company, boasts 180,000 members as of April 2008 and serves many customers with luxury vehicles (www.zipcar.com).

The total current U.S. membership in all CSOs is estimated to be nearly 280,000 (Shaheen and Cohen, 2008, unpublished data).

Carsharing is somewhat paradoxical since it is a driving mode, yet it is associated most closely among researchers and industry members with use of what this paper terms "high density" modes (a term that refers to the density of people in each vehicle, as well as the density of the BE that is most associated with each mode) such as walking, bicycling, carpooling, or public transit [4, 5]. Since consumption of carsharing is believed to grow with consumption of high density modes, carsharing could be called, in economic terms, a complementary good to high density travel. The most basic rationale behind the general belief that carsharing and high density auto modes are complementary is that most people can benefit from vehicle access, but only people who rarely need that access because of a lifestyle or a BE context favorable to high density modes will elect not to own a vehicle, and will therefore be more likely to find utility in carsharing. From a strictly financial perspective, carsharing is thought to complement high density modes because of its unique financial proposition. In contrast to auto ownership, which is defined by large fixed payments and then very low and mostly hidden per-mile costs, carsharing organizations instead charge a small or nonexistent monthly fee, and then rely on all inclusive per-hour and/or per-mile fees to generate revenue. By selling a mobility service, rather than a product, carsharing organizations can lower transportation costs (in comparison to private vehicle ownership) for users that drive less than approximately 6000 miles per year (this number is as high as high as 10,000 miles by some estimates) depending on local costs [6, 7].

Researchers have also hypothesized that adding carsharing to the suite of available transportation options in a given region could lead to a reduction in overall vehicle ownership levels and vehicle miles travelled (VMT) as vehicle owners first find that they can save money by relying on a mix of high density modes and carsharing, and then begin to reduce their total VMT due to the new economic structure. These predicted reductions in vehicle ownership and VMT are well documented in user populations, although the observed effect on VMT has generally been statistically insignificant [5, 8, 9]. It is possible that the ambiguous results are due to another effect of the carsharing financial structure that tends to increase VMT for low-income groups [4, 8-10].

Carsharing Demand, Supply, and Use

Microeconomic theory states that the optimal price and amount of carsharing in a competitive environment can be predicted by the intersection of the supply and demand curves for the service (Figure 1). However, there are two particularities in the carsharing industry:

- The ability to meet demand is "chunky" since CSOs can only add or subtract whole cars (shown by the lightly shaded triangles in Figure 1, each triangle representing the capacity of one car to meet demand);

- CSOs often offer the same rates regardless of pod location (P in Figure 1). This means that for each location, the only variable that the CSO will adjust to meet demand is to add or remove supply in the form of vehicles.

Using this simple economic model, a researcher can measure the impact of BE and demographic factors on the level of demand by regressing those factors against usage data, since the different levels of demand theoretically result in different equilibrium rates of use. In areas with high demand for carsharing, the entire demand curve will be higher, resulting in a higher equilibrium point, and therefore in greater supply and more observed activity. In areas of low demand, observed use (and likely supply, due to CSO management) will be low. Although simple, this methodology presents a challenge for carsharing research for a number of reasons. The most important of these are: it has been challenging for researchers to directly measure use, since use data is often considered proprietary [9]; it is unclear if the industry is mature enough to have reached that supply/demand equilibrium, especially given the diverse nature of the different neighborhoods and locations in which they place vehicles; and finally, as an emerging industry, CSOs may not be able meet demand for reasons associated with cash-flow or investment.

Previous studies of carsharing and the BE have defined a measure of supply called the carsharing LOS measure, that was presented in the Transportation Research Board's (TRB) Transit Cooperative Research Program (TCRP) report 108 [9, 11]. Although the LOS is a measure of supply (literally the number of carsharing vehicles in a half-mile radius from a given location), it is used as a proxy of carsharing demand; the theory being that the carsharing company will adjust supply of vehicles to best match demand, and the number of vehicles in a given area should therefore be a good approximation of demand. The greatest strength of this method is that vehicle locations and the number of vehicles at each location are available on the Internet for many different CSOs. However, the basic problem with this method is that carsharing companies can only add supply in increments of whole vehicles, and that supply may not be a close match to the actual use and therefore actual demand.

An alternative method, which is the basis of this paper, is to measure carsharing use directly by requesting raw activity data from CSOs. The strength of this method is that the use data is not an approximation. However, it is much more difficult to get the data for obvious reasons, and this study was therefore based upon a dataset from a single CSO. Also, this method relies to a certain extent on the same assumption that underlies the LOS measure: CSOs will respond to high demand by placing extra vehicles in or near an existing pod. This is important because the equilibrium usage (given by the supply and demand intersection in Figure 1) can easily exceed the possible capacity of carsharing given by a single vehicle or location, and if the carsharing operator does not add another vehicle at or near that location, the optimal amount of carsharing service at that location will remain unmet (Figure 1). That said, the advantage of a direct measure in this case is that for any situation in which the supply and demand equilibrium does not exceed the capacity for service, the activity data will give a finer measure of demand than a supply-based approximation such as the LOS measure. In any case where the supply and demand equilibrium exceeds the capacity, both methods will give a poor measure of demand. Since the success of either of these measures depends on the CSO's ability to place extra vehicles in areas of high demand, any restriction on that ability could have an effect on the model results.

The Effect of the Built Environment on Carsharing Demand

Since its inception in the United States, carsharing success has been linked by researchers to BE, as well as demographic factors. Of particular interest to this study, is just this relationship of carsharing to BE factors, which are defined here to include both traditional BE measures, such as building, sidewalk, or road characteristics, and transit services that are slow to change, such as bus routes. Although carsharing has received much attention in the literature because of its theoretically complementary relationship to public transit and other high density modes, very few studies have attempted to quantify that relationship. Partly due to the nature of a young industry and the dynamics of an early-adopter membership, and partly due to a scarcity of publicly available usage data, most carsharing studies have focused on user surveys, and have repeatedly demonstrated that, for instance, many carsharing members are frequent public transit users and live in medium to high density areas [4, 5, 12].

User traits of current user populations (such as transit use) are often interpreted as evidence that carsharing companies will be most successful in areas providing facilities to serve those traits, such as high transit accessibility. This logical jump is clearly stated in the TCRP report [9]:

> "Findings of this research, which included a survey of current car-share members, conclude that the communities most conducive to successful carsharing programs include the following characteristics:
>
> Good transit
>
> Walkability
>
> Lower than average vehicle ownership . . ."

However, the average traits of current members show only that many current carsharing users also, for instance, use public transit, not that pods are necessarily most successful in areas of high public transit accessibility. In fact, although the BE is usually referred to in the carsharing literature as correlated or causal factors in carsharing adoption, as shown in the quote above, to the authors' knowledge only one multivariate study has attempted to quantify the relationship for the U.S. carsharing market [11]. One previous bivariate study of carsharing in North America found that transit accessibility is correlated with carsharing LOS [9]. However, this correlation was not borne out in a multivariate context, where the best reported model (adjusted R^2 of about 0.5) only included only measures of vehicle ownership and the number of people walking to work in the area [11].

The connection between the BE and carsharing is often deeper than a simple factor related to demand, since transit connectivity is in many cases an integral part of the carsharing business model, even to the extent of full integration of carsharing and public transit locations and payment mechanisms [13]. This close relationship between carsharing locations and transit locations raises the possibility that previous studies of carsharing have been to some extent biased by a self-selected member population; since most carsharing members live near the carsharing vehicles they access, vehicles near public transit will tend to serve a population that has chosen to live within close range of that public transit line, and may therefore contain a self-selected group of transit users. Adding to this tricky research issue is that carsharing may be in a unique position as one of the most heavily researched modes relative to its market share (a back-of-the envelope calculation based on the number of North American carsharing research authors yields approximately one researcher for every 32 carsharing vehicles as of 2005). It is easy to wonder if the sheer amount, as well as the early timing of research in comparison to industry growth, has had an impact on many CSOs' vehicle placement strategies. In fact, some carsharing locations were actually begun by researchers, only later to be adopted by private or non-profit operators; the CarLink II study in Stanford, California, transitioned to ownership by Flexcar at the terminus of the research project [14].

Another challenge to studying demand for carsharing is that the public transit industry is not always positive about the potential for carsharing to be a complementary good to public transit. An example of this attitude was the reluctance of the Philadelphia area transit agency SEPTA to work with a for-profit CSO, due to concerns about competition [9]. Since transit agencies often own well-placed parking lots to bring in park-and-ride customers, lack of cooperation between transit agencies and CSOs could result in serious parking restrictions near transit, and could therefore also result in a biased measure of demand and inaccurate study outcomes, not to mention potentially slowing the growth of the carsharing industry as a whole.

Common BE and Demographic Factors

From the papers reviewed for this study, there are a few common BE and demographic variables that have been found in multiple studies to have a statistically significant relationship (from either univariate or multivariate studies) to carsharing, vehicle miles travelled (VMT), or related travel behavior such as walking. In particular the age of residents and the average number of vehicles owned by each household each appeared in numerous studies. Less frequently found as significant were the gender mix, the number of children in each household, household income, the proportion of drive-alone commuters, and the proportion of households in pre-1940 structures. A number of other variables were significant only in a single study, such as sidewalk width, which is of particular interest to this study. A list of all of the factors that went into the analysis, along with information about the spatial scale of the factor (described in the following section) and the sources originally presenting the factors is available in Table 1.

DATA SOURCES

Carsharing Data

The carsharing data were received from the carsharing operator in two parts: the first part was a detailed compilation of all carsharing reservations that had occurred between January 1, 2006 and the date of the data request, which was in June 2007. The second dataset was a compilation of the vehicles rented from each pod since the beginning of operations. The datasets were linked by a unique reservation number, and no personal information about the drivers of the vehicles was transmitted. For the purposes of this study, a "reservation" is defined to begin at the pre-arranged reserved time (reservation times are usually restricted to 15-minute or similar increments), even if the vehicle was not picked up by the user at that time, and to end either when the vehicle is returned to the location, or at the end of the reservation, whichever is later.

The final carsharing dataset was temporally aggregated to the average month for each pod, then spatially aggregated into clusters, as discussed in a following section entitled, "Pod Clustering." There were an average of 16 months of data included in each pod-level average (range 6 to 18). The statistical analysis methodology of multivariate regression, as described in the "Regression Model Development" section, was chosen for this dataset due in part to the large amount of inter-cluster variation in comparison to intra-cluster monthly variation. Over 80% of the variation in the observed data was between, rather than within clusters.

Small-Scale Built Environment Measures

A contribution of this study to the carsharing literature is that it makes use of a relatively new resource, Google Maps (and Google Earth)-based satellite imagery and retail information, to take specific measures of the BE around each carsharing location. The measures recorded for this study include the number of off-street parking and retail locations within a one-mile radius of each pod, the amount of available on-street parking, and the widths of the sidewalks and streets at or nearest the intersection closest to the pod location. The street and sidewalk widths and on-street parking availability were recorded directly from satellite photos.

Explanation of Selected BE Variables

As indicated earlier and as shown in Table 1, a suite of BE factors were recorded for each carsharing location using satellite imagery and data provided by Google Maps and Google Earth. Below are detailed explanations of the two variables that appear in the final model.

Sidewalk Width

This variable is equal to the average width of the sidewalks on the approaches to the intersection nearest to a given pod location. Measures were taken using the Google Earth "Distance" tool, and all measures were taken in feet. This variable is expected to be positively related to carsharing, as sidewalk width may be indicative of pedestrian and mixed-use activity.

Transit Lines

Also included were indicators of the transit network within a buffer zone from each pod or cluster of pods. Bus and rail routes were obtained from the FTA and BTS, respectively. Service metrics were obtained by overlaying the GIS transit data onto carsharing location buffers, and then recording the individual transit lines or rail stops inside each buffer. The measurement was performed separately for bus, light rail, subway, and regional rail. Amtrak data were not included in the analysis. The number of rail lines was included as a rail measure, and the frequency of bus service was included as a bus measure. In addition, numerous other nominal transit indicators were tested, such as the nominal availability of surface and separated rail service. The variable found to be the best predictor of carsharing activity was a four-level nominal variable (as described in Table 1) referred to henceforth as the Rail Service Measure.

The Rail Service Measure measures only the availability of the different services, not their respective levels of service at each location. Bus service was available within a 400 meter (approximately ¼-mile) radius from all of the carsharing locations, and is not explicitly included in the Rail Service Measure.

MODELS AND METHODS

Data Analysis Tools

The initial analysis of the carsharing and Decennial Census data was performed in Microsoft Access, using the query capability to aggregate, filter, or perform calculations on data. The spatial analysis was performed in structured query language (SQL) using the PostgreSQL PostGIS spatial database system, and the results were mapped using the PostGIS database-driven uDIG map server for visual inspection. Statistical analysis was performed using the SAS institute JMP statistical analysis software package.

Census Data Treatment

Census data were obtained from the Year 2000 Decennial Census, Summary File 3 at the tract level (see Table 1). Using GIS, buffer zones around each carsharing location (or group of locations as described in the Pod Clustering section) were generated and intersected with underlying Census tracts in order to take area- and population-weighted averages of the overlapping Census tract values that could represent the specific circumstances of each location.

Pod Clustering

Pods were aggregated into groups using a clustering method that could represent the cumulative demand in a given area. Using visual inspection and the 400 meter radius pod buffer map as a heuristic, it was decided to use 400 meters as a cutoff distance, as this clustering method happened to remove the majority of overlap, but didn't increase the grain of the analysis much, as shown in Figure 2. This clustering radius was chosen in part to retain a reasonably large number of discrete clusters, since the number of clusters is critical for multivariate analysis. In addition, the smaller the cluster size, the more the model can reflect local effects that may be important for carsharing operators. The downside of using smaller clusters is that as the level of aggregation is smaller, the proportion of unexplained variance is probably larger, and the model fit may appear to be worse. In addition, a poor choice of cluster diameter could inadvertently skew results by effectively weighting some areas more than others. Hierarchical clustering was used with the "complete linkages" method in order to generate compact, circular clusters that most closely resemble the typical walking radius buffers used in public transit analysis.

Spatial Integration of the Data Sources

The study used GIS to integrate the three separate spatial levels of Census data, carsharing cluster level data, and carsharing pod level data (see Table 1 for the factors relevant to each level) into a single statistical analysis, as shown in Figure 3. On the lowest level are BE data and actual recorded vehicle usage collected for each specific carsharing location. At the highest level are all of the Census factors. At the cluster level is combined: directly recorded transit measures via GIS, aggregated carsharing demand measures and BE measures, and the population weighted tract level SF3 data.

Regression Model Development

A least squares regression model was determined using the complete set of factors shown in Table 1, with feedback from the model residuals, variable collinearity, and the development of new calculated measures, such as the various transit LOS measures used in this study. Since the pool of candidate explanatory variables was already chosen using conceptual considerations, the process of selecting the variables for the final model was guided mainly by statistical considerations. The exhaustive method used in this study was to run over 2 million distinct models, and then pick the best model from each level of parameters using the R^2 criterion. The models were then tested to determine the one with the highest adj. R^2. Finally, non-significant terms were provisionally removed if they didn't overly impact the rest of the model; if the interpretation (such as negative or positive sign, general strength of relationship) of other variables changed, the insignificant variable was retained. The final model was checked for acceptable collinearity, homoscedasticity, and various corrections were made, as explained below.

Transformation of Demand

The demand variable (hours of usage per month) was transformed by taking its natural logarithm to yield more homogeneous variances in the model residuals. This step was taken in response to observed residual variance growth in numerous residual vs. predicted plots of regression models developed for this study.

RESULTS

The best model for this dataset (Adj. R^2 of 0.52) is shown in Figure 4 and includes street width, a nominal rail LOS measure, the percentage of drive-solo commuters, the percentage of households with one vehicle, and the average age of the pods that constitute the cluster. The adj. R^2 of 0.52 is slightly higher than the value of 0.50 published in the recent TCRP report, and is considered good for datasets like this one, involving fairly disaggregate cross-sectional data. All variables in the model are significant to the 5% level with the exception of parts of the Rail Service Measure, which were significant to the 10% level.

Discussion

The results of this study confirm previous findings that neither density nor strictly demographic factors play an overt role in the success of carsharing locations [11]; however, this study also adds numerous findings to the existing carsharing literature. The variables that were best at explaining the level of carsharing demand were all to be expected given previous studies [8, 9, 11], with the notable exception of the public transit variable.

The proportion of commuters that drive alone is negatively related to carsharing, which makes sense, and is expected given that these people would generally already be vehicle owners, and in addition, high levels of vehicle commuting tend to signify a neighborhood that has poor public transit or other high density mode amenities. This result indirectly supports the notion that high density auto travel and carsharing act as economic complements.

The proportion of single vehicle households is positively related to carsharing. This makes sense because with only a single vehicle in the household, there may be occasional need for a second vehicle. This result also indicates that carsharing could be a compliment to high density auto travel, since it indicates that areas with households that already share vehicles have higher demand for carsharing.

The age of the carsharing cluster is positively related to usage. Although to the knowledge of the authors, this variable has not been included in previous studies, it is reasonable to assume that the market for carsharing in a specific area will grow over time as people find out about the service and make lifestyle adjustments to best make use of the service.

This is the first study of carsharing to the authors' knowledge to use direct BE measures, therefore street width does not have much of a history as a metric. It is significantly and negatively related to carsharing, however. The authors postulate that street width may be an indicator of both the pedestrian environment in particular (where narrow streets are more pedestrian friendly and wide streets are less pedestrian friendly), and the land use type in general, as narrow streets tend to denote older residential or mixed-use development, and wide streets tend to denote post WWII construction. In this case, the negative relationship between increased street width and carsharing makes sense from the framework, especially given the close relationship between carsharing and walking behavior that has been observed in other studies [4, 8, 11].

One interesting and new result in this study is the interaction between the nominal rail transit indicator (Rail Service Measure) and carsharing. The measure has four nominal levels, the coefficients of which are interpreted directly (The coefficients are centered around their mean of 0, rather than an arbitrary coefficient. See the JMP handbook for a detailed explanation):

The model indicates that there is a positive relationship between light rail availability and carsharing (the Light Rail Only level has a positive coefficient), but a negative relationship between carsharing and regional rail (the Regional Only level) availability. This finding is surprising, but appears to be stable in the model, notwithstanding the marginal significance of the Regional Rail Only level coefficient (p=0.055), which may be a function of the limited sample size of twelve clusters.

This model outcome is likely the result of one or two different general mechanisms: the underlying data are biased away from showing the true demand near regional rail, or there is an actual difference in demand, rather than simply observed use, between regional rail and light rail locations.

Numerous operational factors that could result in fewer carsharing vehicles near regional rail than a CSO would prefer, possibly biasing the results of the study and resulting in the negative Regional Rail Only coefficient. Some reasons for this could include: lack of contracts that would allow parking in public transit parking lots, very high price of parking in these dense areas, or other restrictions that could have to do with a competitor's behavior. A knowledgeable source inside the study CSO told the authors that the CSO was unable to park as many vehicles near regional rail stations as they wanted to, due to the first and third aforementioned reasons. Previously reviewed evidence that rail transit operators do not always view carsharing in an entirely uncompetitive light also support this explanation.

If the vehicle placement bias does not completely explain the results, the model would indicate that carsharing and local transit are in fact economic complements, as hypothesized, but carsharing and regional transit could act in part as substitutes. Under this explanation, regional public transit accessibility could make carsharing less desirable to residents, since it would reduce their need for other long distance travel. This hypothesis may also be supported by previous research that has designated carsharing as a "missing link" mode between high density modes and private-auto transportation, indicating that the service will have the most success where such a link is in highest demand [9].

An alternative hypothesis has to do with residential self-selection: people who live near rapid rail transit may have chosen to do so specifically so that they wouldn't need to drive, and therefore may make less intensive use of carsharing than people without a preexisting aversion to driving.

Also, as mentioned previously in this paper, carsharing is a young industry (particularly in comparison to existing major transportation modes) and the results of this study could be biased due to either immature or uneven vehicle placement, or a user population that is not representative of the possible future membership.

Next Steps

The transit interaction is interesting, and has realistic explanations in both parking availability and in urban accessibility, but clearly needs to be verified using another method. To help resolve the vehicle placement restriction bias, the demand could be modeled using a truncated model that would account for at least some of the "lost" activity due to parking restrictions. At the very least, a model including information about vehicle placement restrictions could shed light on any relationship between parking restrictions and lack of observed carsharing activity near regional rail locations.

There is a large difference between the 2007 TCRP national model results [11] and the same model using this dataset, where the model consists of the dependent carsharing level of service measure, and two explanatory variables: walk commuters and average vehicles per household. The Adj. R^2 for this dataset is 0.07 and neither coefficient is statistically significant, whereas the Adj. R^2 for the national dataset used in the TCRP report was approximately 0.5. The difference indicates that either the difference between the block level scaling method used in that study and the tract level averaging method used in this study, or the difference in samples, may be having a large effect on results. A useful future study would be to perform an analysis of those factors to find the source of the difference.

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List of Tables and Figures

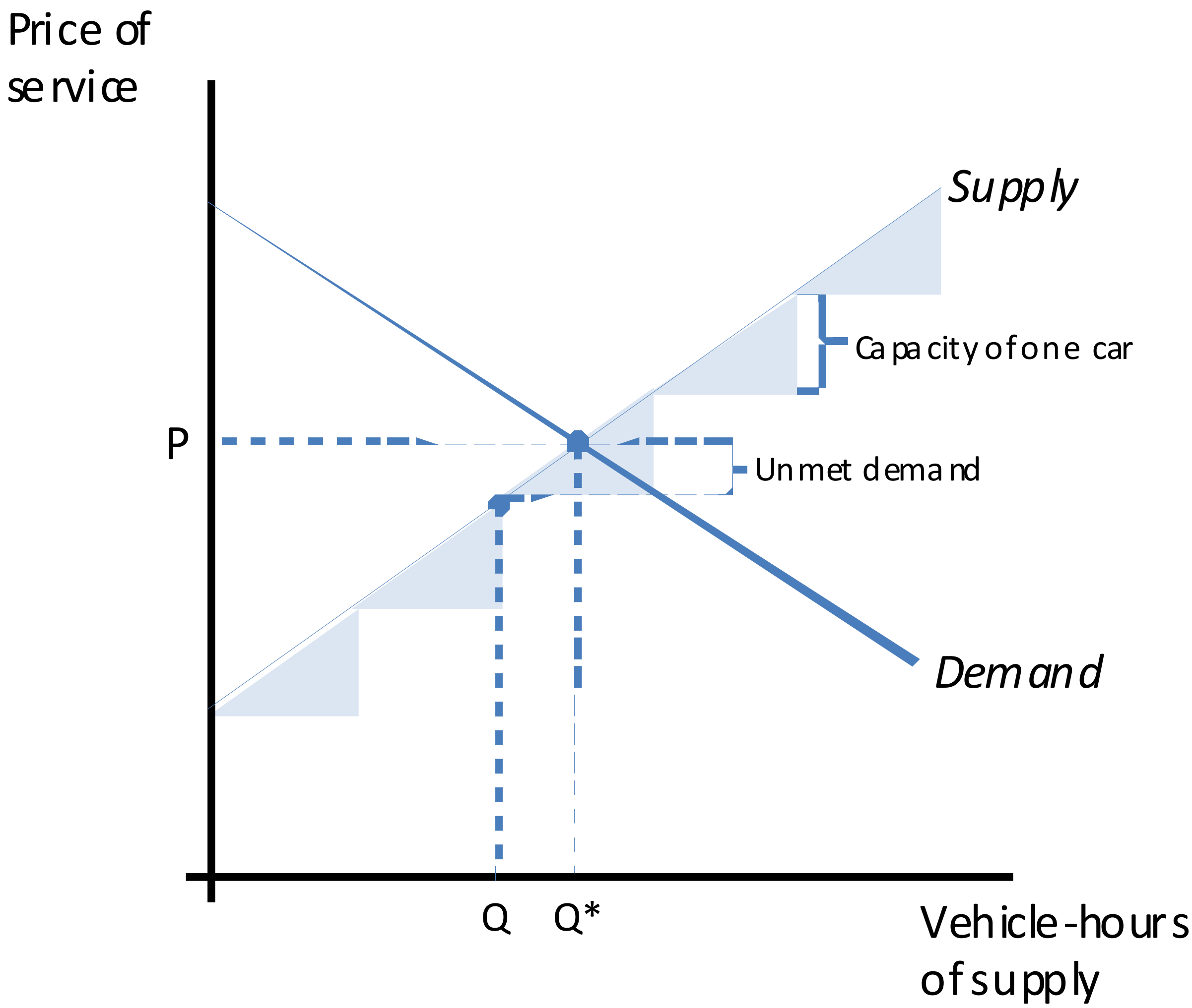

FIGURE 1 Theoretical Carsharing Supply and Demand Curves. P represents the price per hour of carsharing, and Q represents the supply of vehicle-hours. Q* represents the optimal supply for a profit maximizing business.

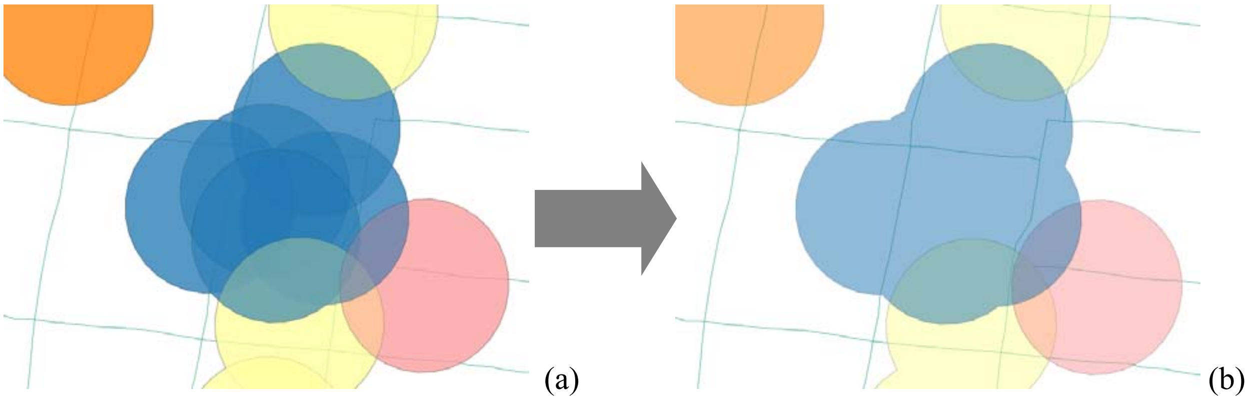

FIGURE 2 Clustering example showing a ¼ mile (400 meter) radius cluster diameter. Un-clustered, heavily overlapping pods are shown in (a), and the resulting cluster shapes in (b).

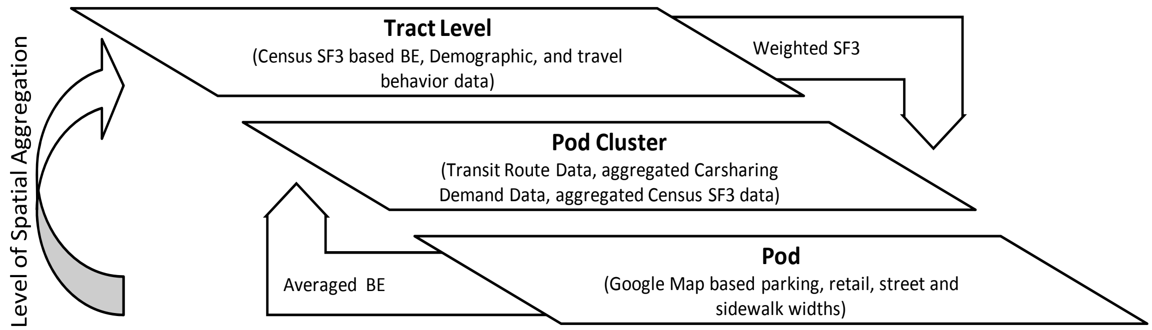

FIGURE 3 Data Integration.

Dependent variable: log (Average monthly hours of use)
Summary of Fit

R^2	0.60
R^2 Adj	0.52
Root Mean Square Error	0.52
Observations	44

Estimates
Nominal factors expanded to all levels

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.78	0.51	13.35	<.0001
Carsharing pod age (Months)	0.0119	0.00453	2.63	0.0124
Commuters that drive alone (%)	-4.48	1.11	-4.02	0.0003
Street width (Feet)	-0.0243	0.00830	-2.93	0.0059
Households with one vehicle (%)	4.39	1.38	3.18	0.0030
Rail Service Measure [Regional Rail Only]	-0.28	0.14	-1.98	0.0549
Rail Service Measure [Combined Rail Service]	0.38	0.20	1.88	0.0678
Rail Service Measure [Light Rail Only]	0.37	0.16	2.39	0.0221
Rail Service Measure [No Rail Service]	-0.47	0.14	-3.29	0.0023

FIGURE 4 Best Carsharing Demand Model.

TABLE 1 Variables tested in the analysis.

	Variable Description *(All variables are proportions unless otherwise noted)*	Hypothesized Relationship to Demand	Spatial Level	Mean Value *(mean value for spatial units used in the analysis)*	Source(s) Showing Significance in Same or Similar Variable
Demographics Related Factors	1 person households	+	tract average	0.45	[9, 15]
	2 person households	-	tract average	0.31	
	Female	+	tract average	0.48	[16-18]
	White householders	+	tract average	0.59	[15]
	Households with children	-	tract average	0.10	[8, 16]
	Population between the ages of 22 and 24	+	tract average	0.06	[8, 16-19]
	Population between the ages of 25 and 29	+	tract average	0.13	
	Population between the ages of 30 and 34	+	tract average	0.12	
	Households earning more than 100k	+	tract average	0.18	[9]
	Average household income	+	tract average	$65,000	[15-17]
	Population with at least bachelor's degree	+	tract average	0.48	[17]
Transportation Related Factors	Average age of carsharing pods in cluster	+	pod average	-	
	Households with no car	+	tract average	0.34	[8, 9, 11, 16, 18]
	Households with 1 car	+	tract average	0.43	
	Households with 2 cars	-	tract average	0.18	
	Average vehicles available per household	-	tract average	0.96	
	Commuters that commute by walking	+	tract average	0.15	[9]
	Commuters that commute by driving alone	-	tract average	0.35	[8, 9]
	Commuters that commute by public transit	+	tract average	0.30	[9]
	Total number of walk commuters	+	tract average	1100	[11]
	Average commute time	-	tract average	27	[15]
Built Environment Related Factors	On-street parking metric (0-16)	-	pod	6.6	[16]
	Retail stores within 1 mile radius	+	pod	79	
	Parking garages or lots within 1 mile radius	+	pod	44	[16]
	Average sidewalk widths near the pod (ft)	+	pod	11	[16]
	Width of the streets near the pods (ft)	-	pod	38	
	Peak-hour bus frequency (busses/hour)	+	pod cluster	54.8	[15, 16, 18]
	Off-peak bus frequency (busses/hour)	+	pod cluster	24.2	
	Street-level rail lines in the cluster (#)	+	pod cluster	1.5	
	Availability of street rail service (0-1)	+	pod cluster	0.34	
	Number of subway or elevated rail lines	+	pod cluster	3.4	
	Availability of separated rail service (0-1)	+	pod cluster	0.95	
	Rail service measure (Calculated Nominal Variable: No Rail, Light Rail Only, Heavy Rail Only, Combined Service)	increasing from first to last factor	pod cluster	NA	

TABLE 1 Variables tested in the analysis.

Variable Description *(All variables are proportions unless otherwise noted)*	Hypothesized Relationship to Demand	Spatial Level	Mean Value *(mean value for spatial units used in the analysis)*	Source(s) Showing Significance in Same or Similar Variable
Household density (households per acre)	+	tract average	18.75	[9, 18]
Housing units built before 1940	+	tract average	0.51	[9, 16, 18]

TABLE 2 Rail Service Measure Coefficients. Dependent Variable : log(Average monthly hours of use).

Rail Service Measure Factor Level	Estimate	N
Regional Rail Only	-0.28	12
Combined Rail	0.38	9
Light Rail Only	0.37	6
No Rail Service	-0.47	17