Driving Smart: Carsharing Mode Splits and Trip Frequencies

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ABSTRACT

Carsharing is a type of vehicle rental that allows individuals to rent vehicles from a fleet on an hourly basis, allowing those without a personal vehicle to have access to a car as needed. Carsharing trip frequencies and mode share are of value to both carsharing and metropolitan planning organizations, and this analysis provides innovative techniques to estimate the number of trips taken and the share of total travel completed with free-floating carsharing. Average household income, and household sizes have a negative effect on the modal split of free-floating carsharing, and land use density has a positive effect; all of these results confirm previous analyses. When considering the number of rentals instead of modal share, both household and employment densities have a positive and strong effect on the number of rentals. Males are found to make slightly more trips via carsharing than are females, and carshare members between the ages of 20 and 39 also have increased trip rates. While these results are based on a free-floating carsharing system in Austin and may not be applicable to all carsharing systems in all cities, they nonetheless provide a basis for enhanced mode share modeling of carsharing in general.

1. INTRODUCTION

Carsharing is a specific type of car rental that allows individuals or businesses to rent vehicles by the hour or minute, as opposed to traditional car rentals that are based on day- or week-long rentals. Most carsharing organizations charge a membership fee, a deposit that is refundable upon leaving the organization, hourly fees, and mileage after a certain number of free miles. In return, the carsharing service handles all costs of ownership, including purchasing, maintaining, insuring, and fueling the vehicle. This type of service draws users who only need a car on an occasional basis, allowing these individuals the benefits of private vehicle access without the demands of car ownership. In combination with walking, bicycling, and carpooling, and public transit access, carsharing allows an individual a variety of transportation alternatives beyond private vehicle use.

In October 2008, Daimler began a carsharing pilot program in Ulm, Germany, beginning the era of free-floating carsharing programs. Daimler provided a fleet of 200 diesel-powered Smart ForTwo vehicles and allowed members to rent the vehicles by the minute. Using GPS technology, the service tracks the locations of all vehicles relative to a boundary called the geofence, which encompassed the central part of the city. While vehicles could be driven outside of the geofence, rentals could only be ended when the vehicle returns to the fenced zone, thereby keeping available vehicles within a reasonably limited area. This freedom to park the vehicles anywhere, allowing one-way rentals instead of requiring the driver to bring the vehicle back to its place of rental, is one of the defining characteristics of a free-floating carsharing operation. The charging structure is also different from most carsharing systems; members pay \$0.35 for each minute of their rental, while most existing carsharing plans charge on an hourly basis. Finally, the composition of the vehicle fleet is unique; all of the vehicles are the same type (the Smart ForTwo), as opposed to the variety of vehicle types and sizes provided by most other carsharing organizations. Following its implementation in Ulm and other German cities, Daimler next brought a fleet of gasoline-powered Smart ForTwo vehicles to Austin, Texas, beginning service on November 17, 2009, with a geofence encompassing 32 square miles of central Austin. This paper focuses on Car2Go's first full year of operations (2010) in Austin.

This type of carsharing system is relatively unique in the rapidly-growing carsharing world because it is a free-floating operation; cars do not need to be returned to any particular location, whether their starting parking space or any other designated location. Instead, vehicles may be taken on one-way trips and left wherever is convenient for the user. In this regard, one-way carsharing programs are very similar to the burgeoning bicycle sharing industry; users pick up a bicycle at any station and may return it to any other station in the network. This characteristic of the one-way program results in a number of management issues not yet encountered by other carsharing operators, including that of understanding modal share and frequency of trips made for the potentially one-way trips. This paper provides several model structures that carsharing and metropolitan planning organizations can both use to estimate trip generation rates and mode shares for free-floating carsharing.

2. BACKGROUND AND LITERATURE REVIEW

Analyzing and forecasting modal splits has been part of transportation planning for decades. Most of the emphasis, at least in the United States, has been on the single occupant vehicle (SOV) mode, as that is the dominant mode for most American cities. Less (although still notable) emphasis has been on the other possible modes of transportation – transit, carpooling, walking/bicycling, and other alternatives, including carsharing (Model Validation, 2011).

Carsharing trip purposes may be of key importance in understanding carsharing mode splits, as they have generally been found to be unlike traditional work-based trip purposes used in existing mode split models. Use of carshare vehicles by individuals is primarily for personal business, such as errands and doctor's appointments, and for social and recreational trips (Cervero, 2002). In areas with limited personal vehicle availability, the primary use of carsharing is local residential and neighborhood use (Barth et al., 2006).

Free-floating carsharing systems are the subject of recent research efforts, many of which do focus on the Car2Go program in particular. Firnkorn and Müller (2012) look at the potential environmental effects of free-floating carsharing programs using Car2Go's Ulm system as a case study; they find a slight reduction in averageCO2 production for each Car2Go member, similar to that found in traditional carsharing systems. Other studies have assessed various methods of analyzing Car2Go's impact (Firnkorn, 2012). The vehicle relocation issues facing free-floating carsharing systems, including Car2Go, have been the focus of recent optimization efforts, including Kek et al (2009), Weikl and Bogenberger (2012), Correia and Antunes (2012), and Jorge et al. (2013). However, little work has been done looking at the mode share split of carsharing, either traditional or free-floating, as compared to other transportation modes.

Much of the mode choice modeling that has been done to date has been in the form of discrete choice modeling, in which each travel alternative is a possible option for a traveler. Other analyses have considered the effect of new facilities or policies on one particular mode's share; for example, the impact of a new bus lane on transit mode share, or increased bicycle parking on bicycling mode share. In this analysis, the effort is not in discrete choice modeling, but instead in estimating the share of travel by carsharing as compared to all travel; in other words, focusing on one mode only. Ideally, this analysis will serve as a basis for future mode share modeling that includes carsharing along with SOV, transit, and non-motorized modes.

3. MODE SHARE ANALYSIS

Because there is little previous research on mode splits for any type of carsharing, free-floating or not, this analysis considers three different methods to determine accurate mode share models. The first method uses all rentals that occurred during the period in which Car2Go was open to the public (June through December of 2010), as compared to the total of all trips predicted by the Capital Area (Austin, Texas) Metropolitan Planning Organization (CAMPO) for the same time period. The second method considers only trips that were "true trips," one-way trips with no intermediate stops. The third method assumes that carshare users make the same number of total trips per day as non carshare users, and thus simplifies the analysis to studying people instead of trips.

In each case, the mode share used as a dependent variable was calculated with the help of data provided by CAMPO. CAMPO provided estimates of total weekday (Monday through Thursday) trips made to and from each traffic analysis zone (TAZ) in the metropolitan area, broken down by mode. Modes included personal vehicle, transit, and non-motorized, and summing these three modes resulted in a total number of estimated trips, which could then be summed across all destinations to determine the total estimated trips starting in each geofence-bound TAZ.

As a comparison, Car2Go rentals (either all rentals or only the true trips, depending on which analysis was being completed) were also summed across all geofence TAZs. Exploratory analysis confirms that, during the second half of 2010 while the program was open to the public, usage was fairly consistent across all seven days of the week. Therefore, the total number of rentals (or true trips) per TAZ could be divided by the total number of days between June 1 and December 31 (214) to find the average number of rentals (or true trips) per day. Comparing this number of daily Car2Go rentals per TAZ to the total CAMPO estimate of trips made starting in the TAZ resulted in the Car2Go mode share.

With regard to the type of modeling used for the mode share analysis, logit models were considered. Because the share of any mode is necessarily between 0 and 1 (or between 0% and 100%), a logit model, which takes a sigmoidal curve shape and restricts the dependent variable to be [0,1] is certainly a consideration. However, least-squares modeling was chosen instead. The mode shares may technically fall anywhere between 0 and 1, but practically, the maximum mode share was determined to be less than 0.7%. Logit modeling would be more appropriate if the data were well-distributed (or at least better-distributed) between 0 and 1. Carsharing currently comprises very small mode shares, both in this data set and in general (see, e.g., Cervero et al., 2007, and Randall, 2011). While its prevalence continues to grow, North American cities are still many years away from carsharing representing a significant share of all travel. Therefore, while mode shares remain in the range of 1% or less, least-squares modeling can describe the mode split as well as any other model structure.

3.1 All Rentals (Maximum Mode Share)

When determining which of the approximately 160,000 Car2Go rentals in 2010 should be included in a mode share analysis, one line of thinking is that all rentals during the public period should be included. Even if the trips were not one-way and/or contained intermediate stops between the rental's beginning and ending, these rentals still involved driving on the city's street network and still provided a means for the renter to travel from point to point (although it may have also been from point to point to point to point).

Both anecdotally and empirically, many carshare rentals do not involve simply traveling from point A to a relatively far-flung point B and leaving the rental behind. When members decide to use a carshare vehicle, they are often making multiple stops: running several errands, visiting friends or doctors, or traveling to a store and returning home with the purchases (Blair and Dotson, 2011; Cervero et al., 2007; Burkhardt and Millard-Ball, 2006). Eliminating consideration of this very large fraction of rentals would limit the usefulness of any mode split analysis, as it would leave a significant number of the rentals unexplained.

Another argument for including all rentals in the analysis (instead of only the one-way direct trips) is that Car2Go is relatively unique in its allowing one-way carsharing rentals. While the data used in this mode share analysis is from Car2Go and thus includes a significant number of one-way trips, most existing carsharing programs require that the vehicle be brought back to its starting location before the rental can be ended. Limiting the mode share analysis to one-way carshare rentals would severely limit the applicability of a mode share model for any other carsharing program currently in existence. On the other hand, inclusion of all rentals, including those that came back to their starting point and those that included intermediate stops, results in a mode split model that is far more applicable to all carsharing organizations instead of only free-floating carsharing.

Inclusion of all rentals in the mode share model will result in what is effectively a "maximum share" model. A region's MPO can assume that no more than these resulting fractions of total trips can reasonably be expected to be made by carsharing. Because the mode share percentages are such small values, some form of data transformation was necessary before running statistical models on the data. The final transformation chosen was a straightforward log(y). Converting these small fractions to their log versions resulted in dependent variables ranging from -1.2 to -5.0. Using a log transformation also provided a significant reduction in the amount of heteroskedasticity (the inconsistent level of variance among data points) in the data.

For this model and all other models described in this paper, a large number of variables were considered for all of the following models. Only variables that were statistically significant were retained in the final models (and the significant variables vary from model to model), but it is important to note that a wide variety of demographic and socioeconomic variables were considered. These variables include the following for each census block:

- Median household income
- Median age
- Average household size
- Average household vehicle ownership
- Percent of the population that is male
- Percent of the population that is white/non-Hispanic
- Percent of the population that is Hispanic
- Percent of the commuting population that uses transit
- Percent of the population in each of the following age brackets: 0-10, 11-20, 21-30, 31-40, 41-50, 51-60, 61-70, and 70+.
- Percent of dwelling units that are rented
- Percent of the population below the poverty level
- Percent of the population working outside the home
- Household density per acre
- Indicator variable for block being within the geofence

The final model specifications are shown in Table 1.

TABLE 1 Mode Share Model Specifications (All Rentals)

Variable	Coef.	Std.Err.	Sig.
Constant	-2.496	0.151	0.000
Household and employment density (per acre)	0.0039	0.001	0.085
Average household size	-0.134	0.058	0.022
Median household income (in thousands)	-0.0032	0.002	0.115
			N=126
			Adjusted R^2: 0.057

The independent variables used in the "all rentals" mode share are provided by CAMPO and are used in their existing mode share models. Because of this similarity to the official mode split models used in the Austin metropolitan area, these carsharing models are likely to be easy to introduce into CAMPO's models.

The adjusted R_2 value for this model is 0.057, relatively low. While each of the three independent variables used in the model are somewhat statistically significant, the model as a whole explains only a small fraction of the total variability in the dependent variable. The implications of this will be discussed further, but indicate that residential demographics may not be an appropriate set of variables for a robust analysis of carsharing mode share.

Average household size and median household income both have a negative effect on the expected carsharing mode share. Household size is an expected result, in part because household size and number of children are closely correlated variables, and those with children have been shown to be much less likely to use carsharing on a regular basis. A negative coefficient on income is not a surprising result either. Housing and employment density has a positive effect on expected mode share; this is also consistent with previous carsharing literature (see, for example, Stillwater et al., 2009, and Millard-Ball et al., 2005).

3.2 True Trips (Minimum Mode Share)

As an alternative to the mode share analysis completed above, a second methodology is to consider only trips that are one-way and direct. Not all of the rentals in the data set fit this condition; many of the rentals were either round trips or trip chains. The data did not provide information about when or where the vehicle stopped, but only where the trip began and ended. As a result, specific information about each trip in a chain or each leg of a round trip could not be determined; instead, the data only showed one relatively long trip with an unknown number of stops along the way.

Additionally, because the data provided by the MPO is in the form of these "true trips," a comparison of this sort allows for the most appropriate mode share calculation. This methodology most directly compares "apples to apples"; in including all types of trips, the previous model's comparison of Car2Go rentals to CAMPO trip estimates could be said to compare "apples to apples-and-oranges-and-bananas."

In determining which trips counted as "true trips" for this mode share analysis, the rental records were subjected to a series of eliminations. First, only rentals that ended at least two blocks (approximately 0.3 miles) from their starting point were considered. 8,331 rentals with an average speed of less than 5mph were removed, as were 1,283 rentals with duration of more than 120 minutes. 14 rentals reporting average speeds of more than 60mph were also removed; most of these were reporting speeds in excess of 100mph and were likely faulty data points. Finally, the total (straight-line) distance between the start and end points of the rental was calculated and compared to the total miles driven during the rental. Accounting for the fact that network distances are longer than straight-line distances, 16,407 rentals where the ratio of straight-line distance to total distance driven was less than 0.5 were discarded. This procedure resulted in 58,528 true trips, as compared to a total of 116,580 rentals during the same period. These trips had the characteristics shown in Table 2, all of which are consistent with an individual driving directly from Point A to a different Point B.

TABLE 2 Characteristics of True Trips

Characteristic	Median	Mean
Duration (minutes)	11.0	13.35
Miles traveled	2.0	3.01
Average speed (mph)	12.0	13.54
Ratio of distance between start/end and miles traveled	0.75	0.79

As with the analysis of all rentals, the heteroskedasticity in the variables is quite pronounced and a transformation of log(y) was used.

This "true trip" mode share model acts as a minimum likely mode share, as it is developed on a particular subset of the total rentals made during the analysis period. The most accurate possible mode split model is probably between the two methodologies. However, the models for "all rental" and "true trip" mode shares are very similar to one another; the model specifications for true trip mode share are shown in Table 3.

TABLE 3 Mode Split Model Specifications (True Trips)

	True Trips			*All Rentals*
Variable	**B**	**Std.Err.**	**Sig.**	***Coef.***
Constant	-2.757	0.149	0.000	*-2.496*
Household and employment density (per acre)	0.0028	0.001	0.128	*0.0038*
Average household size	-0.140	-0.057	0.016	*-0.134*
Median household income (in thousands)	-0.0034	0.002	0.074	*-0.0032*
N=126 Adjusted R^2: 0.086				

The most significant result of this model specification is its similarity to that of the all-rental model, which includes the same three variables. The coefficients of the "all rentals" model are shown in the rightmost column of Table 3. To three decimal places, the coefficients for income are identical, and the coefficients for density differ by only 0.001. Average household size has a slightly more negative effect on the true trip mode split than it does for the all rental mode split, emphasizing that the true trips mode split is a minimum split, while the all rental mode split is a maximum. The adjusted R^2 of this model is 0.086, a slight improvement over the all rental model at 0.057, but still low. Residential demographics again result in a less-than-robust mode share model.

Because these two models are so similar, the distinction between "true trips" and all rentals is not as important as it may have initially seemed. This is, of course, based on a data set where the mode shares were very small – most were under half of a percent. As the mode shares attributable to carsharing increase over time and in other cities with more and larger carsharing programs, these numbers may vary. However, despite its rapid growth around the United States in recent years, trips by carsharing still represents a very small proportion of all trips taken. Therefore, these results are likely to be applicable in most current carsharing metropolitan areas, and are likely to be valid not only today but for many years in the future.

3.3 Person Shares as a Predictor for Rental Frequencies

Another methodology for determining mode share is to assume that carshare members make the same number of trips on a daily basis as do those who are not carshare members. If the number of trips made per day is the same, then the value of person-trips can be simplified to the value of persons. This simplification allows for an analysis based on demographic characteristics of the residents of census blocks in which trips were made (that is, census blocks within the geofence). These demographic characteristics are combined with membership rates in the same block when considering the number of rentals that occur in the block. After all, only the members will be making the rentals; the general population will not have access to the carshare vehicles. Using the ratio of total rentals in 2010 to members in a census block, the ordinary least squares model of Table 4 emerges:

TABLE 4 Rentals per Member Model Specification

Variable	B	Std.Err.	Sig.
Constant	0.085	0.009	0.004
Percent of population aged 20-39	0.062	0.020	0.003
Household density per acre	0.0014	0.000	0.000
Percent of population that is male	0.108	0.025	0.000
Average household size	-0.932	0.452	0.039
N=2,890 Adjusted R^2: 0.161			

An increasing percentage of the population between ages 20 and 39 increases the total number of rentals per carshare member, as does an increasing household density (and, one assumes, the corresponding land use density). Increasing household size, on the other hand, has the expected negative effect on total number of rentals per carshare member; again, household size is closely correlated with number of children per household, and those with children have been shown to be much less likely to use carsharing regularly, if at all.

On the other hand, the share of the population that is male becomes statistically significant here. An increased proportion of males in a census block increases the estimated number of rentals undertaken per carshare member in the census block. While there has not been shown to be a consistent difference in the proportion of males and females who are member of carshare programs in either this research or previous studies, this finding indicates that males who are members are likely to make more trips than are females who are members.

Both of these analyses of vehicle rental frequencies is limited, as many of the renters in any given census block are likely to be those who work in the block (or a nearby block) but reside elsewhere. As a result, this set of variables, as is the case with all of the models developed so far, is not particularly robust, despite the low significance values for each variable. The model's adjusted R^2 value is only 0.161, indicating that it describes only about 16% of the total variance in the data. This is almost certainly due to the types of trips being made. Traditional mode-share analyses are designed to consider primarily home-based trips (and especially home-based work trips), as most trips made by North American households are home-based trips or trip chains. Home-based work trips are also the most regular and predictable trip type and thus relatively easily modeled. Household demographics are also strong predictors for trips that begin at home.

However, previous research has consistently found that carshare users rarely use the vehicles for home-based work trips (see, e.g., Cervero et al., 2007, and Shaheen et al., 1998). Without a large proportion of home-based trips, the available demographic variables produce a much less robust trip estimate. While there is no way to completely determine the purposes of the trips made during Car2Go's first year of operation, a time-of-day analysis for the rentals strongly supports the case that the trips are not home-based work trips. See Figure 1.

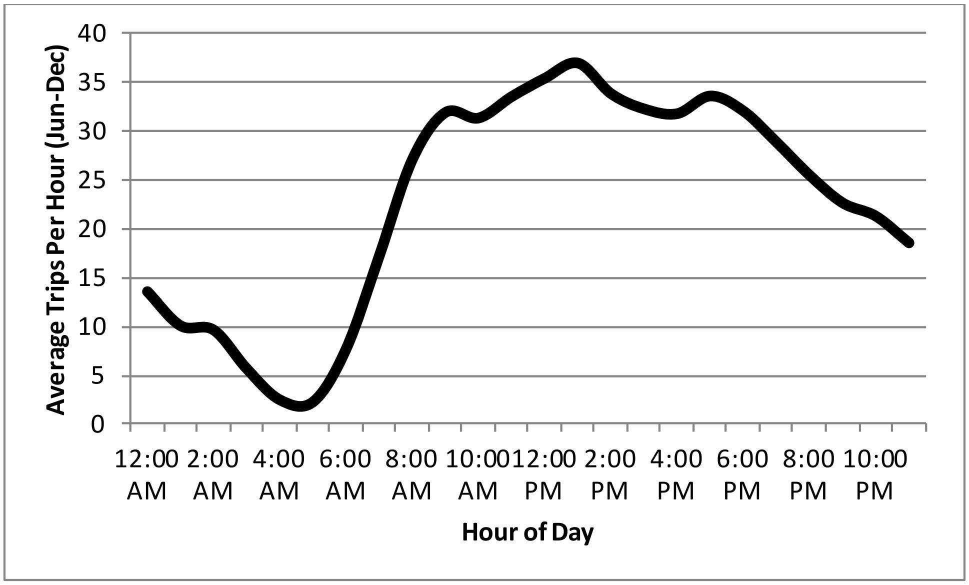

FIGURE 1 Average Rentals by Hour

If a significant proportion of the Car2Go trips had been home-based work trips, a graph of usage by hour of day would show noticeable peaks during the morning rush hour (approximately 7-9am) and the evening rush hour (approximately 4-6pm). While there are very slight upticks in usage during these hours, the peak usage clearly occurs in the middle of the day (between 12pm and 2pm). The time of this peak supports the hypothesis that trip purposes are primarily not home-based work trips but instead represent users choosing to run errands and shop during their lunch hour. Also, usage remains high throughout the entire day, starting at 6am and only seriously declining by midnight, again supporting the hypothesis of Car2Go (and carsharing in general) serving primarily home-based non-work and non-home-based trips.

Because of this consideration, yet another methodology for considering the trip making rates is to set the dependent variable as the total number of daily trips begun in an area, without adjusting for the population or number of members living in the area. The population and membership will instead become independent variables that may or may not prove to be statistically significant. This analysis may be more robust, as it not solely dependent on only the residential attributes of the area but instead considers employment characteristics as well. In order to run this regression analysis, however, the area of study must change to TAZs instead of census blocks; employment information is not available on the census block level. The specifications for this linear regression model can be found in Table 5.

TABLE 5 Trip Starts – Linear Regression

Variable	B	Std.Err.	Sig.
Constant	1.871	0.580	0.002
Household density per acre	0.484	0.116	0.000
Employment density per acre	0.041	0.012	0.001
N=126 Adjusted R^2: 0.176			

Because the dependent variable is the total number of daily trips originating in a TAZ, the coefficients of this model are simple to interpret. One additional household per acre increases the estimated number of trips made per day by 0.484, and one additional job per acre increases the estimated number of daily trips by 0.041. While the two coefficients vary by a factor of ten, it should be noted that, in general, a greater number of jobs can be in the same area as one household. For example, one floor of a large office building could easily house a few hundred employees, while the same square footage is unlikely to contain more than fifteen or twenty households (in the form of apartments or condominiums). Overall, and unsurprisingly, areas with high residential density and/or high employment densities are predicted to generate large numbers of carshare trips each day. High employment densities can offset low residential densities, providing an explanation for the high levels of carsharing trips in CBD zones with little, if any, residential population. This model also provides further evidence for the hypothesis that a large proportion of carshare trips are not home-based but instead work-based trips.

4. CONCLUSION

Mode share modeling for carsharing is an innovative methodology introduced in this paper. Because little has been done previously to analyze carsharing mode splits, this analysis looks at three separate methods: using all carshare rentals compared to all travel (as estimated by the local MPO) as a dependent variable, using only one-way carshare rentals (true trips) compared to all travel, and looking at person-shares of travel as opposed to trip-shares. All rentals and true trips result in very similar model specifications, with increasing density, household size, and income all resulting in lower mode share. When considering person-shares, the focus is on number of carshare trips made instead of the fraction of total trips that were made by carsharing. In this analysis, the proportion of members in a zone is of utmost importance when considering trips per member, but in terms of total number of trips, the key variables are household and employment densities. These two density values provide a reasonably robust measure of the total carshare trips in any zone.

While the independent variables used in the models described here are statistically significant, the models overall are not particularly robust. In addition, many of the variables that have long been shown to be connected to carsharing use in previous literature and empirical evidence (including education, vehicle ownership, and transit use) did not prove to be statistically significant with this data. This is likely due to the difficulties inherent in using established mode share analysis techniques on the relatively new carsharing alternative. In addition, the city of Austin’s land use and transportation patterns are markedly different than many cities where carsharing has been successful and examined; Austin is more sprawling and car-dependent than many of the traditional carsharing cities, including New York, San Francisco, and Washington DC. However, the presence and moderate success of free-floating carsharing in Austin indicates that carsharing is likely to also see some success in the wide array of American cities which more closely resemble Austin’s land use patterns than the small number of large, urban, and dense cities where carsharing has already proven viable.

Because most of the mode share analysis done to this point focuses on home-based work trips but few carsharing trips are home-based work trips, opportunities exist for enhanced analysis of carsharing mode splits. A better understanding of trip purposes of carsharing users would provide a basis for the development of more robust carsharing mode split modeling. This paper provides a mode share analysis exclusively dedicated to carsharing, a mode that has previously been overlooked in similar analyses. Carsharing is currently a very small proportion of all trips, even in metropolitan areas where carsharing organizations are numerous and highly successful. However, this transportation alternative is growing rapidly around the country and metropolitan planning organizations would be well-served to include carsharing as one of the considered transportation alternatives, along with driving, transit, non-motorized modes, and other small-share alternatives. The analysis provided here provides a basis for inclusion in such metropolitan travel models, allowing carsharing to be considered as a serious alternative to owning a vehicle and planning agencies to establish the needed circumstances to support a robust carsharing organization.

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