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Free-Floating Carsharing Systems: Innovations in Membership Prediction, Mode Share, and Vehicle Allocation Optimization Methodologies

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Free-Floating Carsharing Systems: Innovations in Membership Prediction, Mode Share, and Vehicle Allocation Optimization Methodologies

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Free-Floating Carsharing Systems: Innovations in Membership Prediction, Mode Share, and Vehicle Allocation Optimization Methodologies

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Free-floating carsharing systems are among the newest types of carsharing programs. They allow one-way rentals and have no set “homes” or docks for the carsharing vehicles; instead, users are permitted to drive the vehicles anywhere within the operating zone and leave the vehicle in a legal parking space. Compared to traditional carsharing operations, which require the user to bring the vehicle back to its assigned parking space before being able to end the rental, free-floating carsharing allows much greater spontaneity and flexibility for the user. However, it leads to additional operational challenges for the program.

This dissertation provides methodologies for some of these challenges facing both free-floating and traditional carsharing programs. First, it analyzes cities with carsharing to determine what characteristics increase the likelihood of the city supporting a successful carsharing program; high overall population, small household sizes, high transit use, and high levels of government employment all make the city a likely carsharing contender. Second, in terms of membership prediction, several modeling alternatives exist. All of the options find that the operating area is of key importance, with other factors (including household size, household densities, and proportion of the population between ages 20 and 39) of varying importance depending on the modeling technique. Third, carsharing trip frequencies and mode share are of value to both carsharing and metropolitan planning organizations, and this dissertation provides

innovative techniques to determine the number of trips taken and the share of total travel completed with carsharing (both free-floating and traditional). Fourth and finally, an original methodology for optimizing the vehicle allocation issue for free-floating carsharing organizations is provided. The methodology takes a user input for the total number of vehicles and returns the allocations across multiple demand periods that will maximize revenue, taking into account the cost of reallocating vehicles between demand periods.

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Chapter 1: Introduction

1.1 Overview

Much of the low-density urban development that has occurred in the United States over the last several decades has been enabled by and designed around the automobile. The resultant automobile dependency has led to a variety of environmental and social problems, including air and noise pollution (Boothroyd, 2012), greenhouse gas emissions (Hankey & Marshall, 2010), traffic congestion (Schrank & Lomax, 2010), and a dependence on foreign oil (Anderson et al., 2011). Additionally, vehicle ownership carries a significant financial burden, with the average vehicle costing its owner $8,775 per year (AAA, 2011), despite its being used less than ten percent of each day (Motavalli, 2011). Most efforts to reduce automobile usage have focused on public transit, but carsharing may help to fill the space that remains between public transit and private vehicle ownership.

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 (Shaheen, 2008). 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.

Carsharing also tends to reduce car ownership and amount of driving over time (Cervero et al., 2007); Zipcar estimates that for every three members, a new car goes unsold (Maynard, 2009). Recent analysis has suggested that carsharing in the United States has taken between 90,000 and 130,000 vehicles off the road, equating to 9 to 13 vehicles per carsharing vehicle (Martin et al., 2010). In owning a vehicle, most of the expenses associated with the vehicle are fixed (purchase cost, insurance, etc.). Because the variable costs of using the vehicles are low, individuals have incentives to drive more than is economically rational (Shaheen, 2008). Carsharing organizations make the complete cost of driving transparent and immediate, allowing a user to make a more informed choice about the cost of their transportation options.

1.2 The Origins of Carsharing

The first carsharing operation began in 1948 in Zurich, Switzerland, as a means for those who could not afford a car on their own to be able to access a vehicle when needed (Harms & Truffer, 1998). Other early operations in the 1970s and 1980s included Procotip in Montpellier (France), Witkar in Amsterdam, Green Car in the United Kingdom, and Bilpoolen in Sweden (Shaheen et al., 1998; Bendixson & Richards, 1976).

Between 1983 and 1986, researchers at Purdue University managed the Mobility Enterprise system. They provided "minimum-attribute vehicles" (lightweight subcompact vehicles with four seats for daily use) to each of 9-12 participating households while allowing the households to have joint access to a fleet of full-size vehicles, including full-size sedans, a station wagon, and a minivan. A household membership fee covered all costs of the vehicles' operation and maintenance except gasoline. Households were also given ten coupons per month for use of a shared vehicle, with an available option to purchase more. The participants realized significant fuel savings despite logging similar both before and after before joining the program. The researchers concluded that shared use of vehicles was a feasible concept, if potentially limited in its application, and confirmed previous theoretical analyses (Fricker & Cochran, 1982) that the optimum number of shared vehicles for 20 households is three.

During the early 1980s, Crain & Associates, a private transportation planning firm, implemented a pilot project called STAR (Short-Term Auto Rental) in San Francisco, supported by Caltrans and the USDOT. Their feasibility study suggested a $0.50/hour and $0.14/mile charges would result in a profitable enterprise that required no government subsidies (Crain & Associates, 1984).

The first commercial operation in the United States began in Portland, Oregon, in 1998 (Katzev, 2003). Today, carsharing is available in more than 1,000 cities around the world (“World Carshare Cities,” 2010) and, as of January 2011, North American carsharing organizations provided about 10,000 vehicles to their more than 600,000 members (Martin & Shaheen, 2011). In January 2011, eighteen carsharing companies joined together to form the Carsharing Association (CSA), an association that “sets the ethical, social and environmental bar for the carsharing industry” (“CarSharing Association Announced,” 2011). In certain metropolitan areas where carsharing has established a strong foothold, these type of organizations are beginning to have an effect on parking policies; some cities, including San Francisco, Boston, and Seattle, are reducing parking requirements due to residents’ easy access to carshare vehicles (Lorinc, 2009; McKeen, 2009). Carsharing is expected to continue to grow rapidly; in North America, the number of carsharing users has doubled every year or two for the last decade (Stillwater et al., 2009). Frost & Sullivan predict that more than 20 million people worldwide will be carshare users by 2020 (50^{th} Anniversary, 2011) and 4.4 million North Americans are expected to be members by 2016 (Zhao, 2010). Previous studies from Germany and Switzerland in the 1990s estimated that the potential market penetration of carsharing is from 3-9% of the total population (Herodes & Skinner, 2005).

The vast majority of carsharing services currently in operation are all round-trip services, requiring the user to return the vehicle to its place of rental before the paid rental period is over. Free-floating carsharing schemes are emerging, however, allowing users far more flexibility in their use of carshare vehicles. For example, by the end of 2012, Paris plans to have a full-scale launch of Autolib, its Bluecar carsharing program, based in part on Vélib, its highly successful self-service bicycle rental scheme (Willsher, 2011). At full launch, the program will have 5,000 electric Bluecars in the city, each of which will be able to travel 250km after one four-hour charge. The rentals are designed to be one-way, with users ending their rentals at whichever of the 1,120 charging stations around the city is convenient for them (Freemark, 2011). However, the rentals will need to end at one of these charging stations located around the city, meaning that the program is only partially free-floating.

1.3 Car2Go

In the early 2000s, Daimler-Chrysler (which has since split into Daimler Auto Group and Chrysler LLC) explored the potential for carsharing but decided that the market was not sufficient for such a service (Herodes & Skinner, 2005). In recent years, however, Daimler has revisited this decision and come to the opposite conclusion.

In October 2008, Daimler joined the ranks of existing carshare operations with its first pilot program in Ulm, Germany, beginning the era of free-floating carsharing programs. Daimler provided 200 diesel-powered Smart ForTwo vehicles for its members and allowed members to rent the vehicles by the minute. Vehicles could be dropped off anywhere within the organization’s geofence, which encompassed the central part of the city. Using GPS technology, the service tracks the locations of all vehicles relative to the geofence; while the vehicles can be driven outside of the fence, rentals can only be ended when the vehicle returns to the fenced zone. This freedom to park the vehicles anywhere, allowing truly one-way rentals instead of requiring the driver to bring the vehicle back to its place of rental, is one of the unique features of Car2Go. Additional unique features include the simplicity of the charging structure: members pay only $0.35 for each minute of their rental, making short rentals very economical, as opposed to renting by the hour under most other carsharing plans. Also, 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 sized provided by most other carsharing organizations. The program was highly successful, with vehicles rented up to 1,000 times per day (Hyperlocal Mobility, 2010). In 235,000 rentals, the vehicles have logged over three million kilometers. 60% of the users are under age 36, and one-third of all drivers between 18 and 35 joined the program during its first year (“1 year old,” 2010).

Following its success in Ulm, Daimler next brought a fleet of gasoline-powered Smart ForTwo vehicles to Austin, Texas, beginning service on November 17, 2009. Initially, service was available only to City of Austin employees under a deal between

Car2Go and the City. Employees were allowed unlimited use of the vehicles for business purposes, with the city paying by the minute for the vehicles' use, and could also open their own personal accounts for non-City use. In return, the City provided Car2Go with free on-street parking at any meter in the 32 square mile operating area (see Figure 1). The City also designated 31 street parking spaces, which can hold 62 of the Smart ForTwos, as dedicated Car2Go spaces (Messer, 2010). The deal was estimated to be worth approximately $85,000 (Hu, 2010), although no money actually changed hands. The service continued to expand during this initial pilot project; Car2Go developed partnerships with other agencies, including the Texas State Preservation Board and the Texas Council on Competitive Government in the spring of 2010 ("Car2Go Partners with State of Texas," 2010). On May 21, 2010, Car2Go opened to the general public, and by the end of September 2010, Car2Go had registered more than 10,000 members, half of which were between 18 and 35 ("Austin's Car2Go Reaches," 2010) and logged over 80,000 vehicle rentals (Motavalli, 2010). In November of 2010, the city voted to extend its contract with the Car2Go on a month-to-month basis for up to one year (Alberts & Vess, 2010), and in 2011, the program became permanent ("Car2Go Completes," 2011).

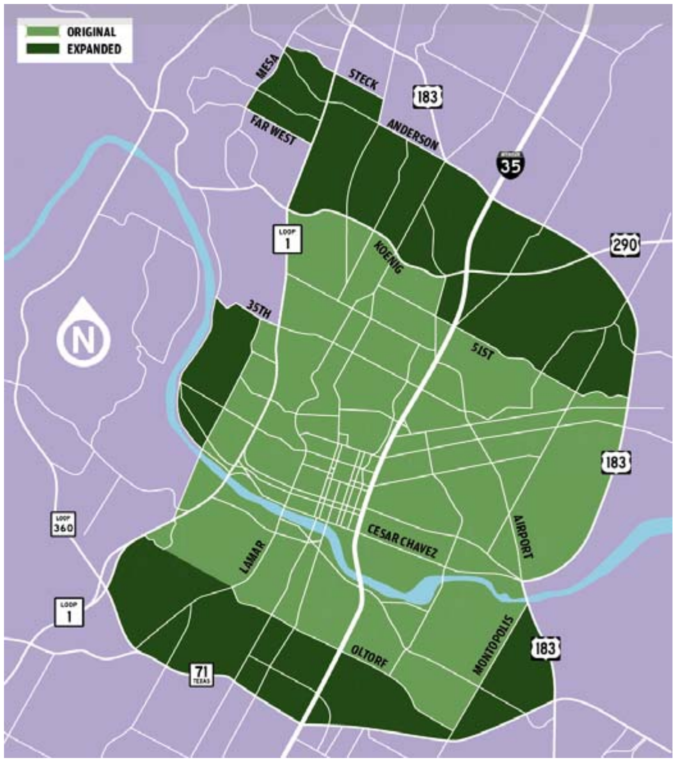

Figure 1: Car2Go Operating Area

Part of Car2Go's uniqueness is that its fleet is comprised of only Smart ForTwo vehicles, as opposed to other carshare operators that tend to provide a variety of vehicle types. The Smart ForTwo vehicle has a very distinctive appearance, commonly described as "cute," which will help the vehicle to stand out from other carshare vehicles, and its uniqueness may also draw increased interest from potential Car2Go members. Initially, Car2Go vehicles were concentrated in two primary locations: the central business district (CBD) of Austin and the University of Texas at Austin (UT). According to its promotional literature, Daimler suggests that Car2Go would be an appropriate service for those who primarily drive alone, who occasionally need a car for short trips, and who would like the car to be "ideally, right around the corner" (Car2Go, 2011).

In addition to its Ulm and Austin operations, Daimler announced in August of 2010 that it would be testing its service in Vancouver, British Columbia. Tests of Car2Go's in-vehicle technology ran through October 2010 and were being conducted in partnership with a variety of partners, including the Vancouver Public Library, the Vancouver Film

School, Bard on the Beach Shakespeare Festival, and members of the University of British Columbia (Blanco, 2010). Full service began in Vancouver on Saturday, June 18, 2011.

On November 18, 2011, Car2Go also began operating in San Diego, this time using a fleet of 300 electric Smart ForTwos. The vehicles are all-electric and have a fully-charged range of about 84 miles; drivers can park the vehicles at any on-street parking space or at one of the 1,500 electric vehicle charging stations around town (Hawkins, 2011). Car2Go also introduced two electric vehicles to its Austin fleet in early 2012 (“Car2Go completes,” 2011).

In addition to its North American operations, Car2Go is also expanding throughout Europe. In October 2010, the company announced an expansion into Hamburg, Germany, its largest city to feature full-service carsharing, and into Vienna, Austria. In Hamburg, the company is partnering with EuropCar to provide logistics and support, likely to eventually result in a larger variety of vehicles being made available than in other Car2Go cities so far (Motavalli, 2010). While the vehicles in Ulm were diesel ForTwos, the Hamburg vehicles are gasoline-powered, and the Ulm vehicles will be replaced with gasoline-powered vehicles as well. In Amsterdam, Car2Go is providing a fleet of all-electric vehicles. In the next decade, Car2Go expects to be operational in more than 50 cities worldwide (“Car2Go completes,” 2011).

Car2Go represents a number of firsts, including the first entry of a major car manufacturer into the carsharing market. Existing carsharing operations have not been vehicle- or manufacturer-specific, instead purchasing a range of vehicle types and manufacturers. Daimler’s system is also unique among existing carsharing operations in that it is a free-floating operation; cars will not need to be returned to any particular location, either their starting point or any other designated Car2Go location. Instead, vehicles may be taken on one-way trips and left wherever is convenient for the user. This characteristic of the program results in a number of management issues not yet encountered by other carsharing operators, particularly that of vehicle allocation (and reallocation).

Car2Go is no longer alone among vehicle manufacturers in launching limited-vehicle carsharing; Fiat Group has recently undertaken a similar endeavor to Daimler. While Fiat is not developing and managing its own carsharing operation as Daimler has done, it has partnered with Hertz's Connect carsharing program in the United Kingdom to make Fiat's popular 500 and Alfa Romeo MiTo the primary vehicles for Hertz Connect throughout the UK ("Fiat Connects," 2010). Fiat sees this as an excellent marketing opportunity, as the carsharing organizations put vehicles "in the hands of young, environmentally-conscious individuals who are free-thinking about the car they want to drive" ("Fiat Connects," 2010). Initially, the company has provided Hertz with 170 vehicles, eventually intending to provide up to 500. Further, Fiat has developed special terms for Connect users who later wish to purchase a Fiat for their own personal use. Other European car manufacturers are also moving in the carsharing direction. Volkswagen has developed Quicar, its own carsharing program, with initial operations in Hanover. At the beginning, there are 200 Volkswagen Golf vehicles at 50 pick-up and drop-off locations throughout Hanover. Eventually, Volkswagen intends to include its Caddy and Beetle models in the available fleet (Loveday, 2011). On the American side, the capital venture division of General Motors has announced its interest in investing in a carsharing operator (Garthwaite, 2010).

Free-floating carsharing is no longer limited to Daimler's Car2Go. In April 2011, BMW began its DriveNow program in Munich. DriveNow uses a fleet of BMW 1-series and Mini vehicles, as well as a handful of vehicles that many users might not be able to buy outright, including the manufacturer's flagship 7-series sedans (Fuhrmans, 2010). These vehicles are priced approximately 29 cents per minute with an additional option of paying 10 cents per minute to "hold" the vehicle during intermediate stops (Drive Now, 2011). DriveNow offers these one-way vehicle rentals within a ring around Munich, very similarly to Car2Go; the initial fleet size of 300 vehicles means that an individual will usually need to walk no further than 500m to reach the nearest DriveNow vehicle (Boeriu, 2011).

1.4 Dissertation Outline

While the possible scope of research on the operating characteristics and effects of free-floating carsharing is vast, this dissertation focuses on a series of models that could be used to identify and operate a successful free-floating carsharing enterprise. Chapter 2 discusses the data used as a basis for most of the modeling, describing its acquisition and performing exploratory analysis. Chapter 3 attempts to better understand the differences among metropolitan areas with and without carsharing organizations using binary logit modeling to examine characteristics that make cities more likely to be home to any type of carsharing program. Chapter 4 provides a methodology, new to academic literature, to predict carsharing membership throughout a metropolitan area, based on demographics of the area and characteristics specific to the carsharing operation. Chapter 5 is also a new methodology, providing an analysis of the carsharing mode split and rental frequencies, based on the data provided for the Car2Go program in Austin. Chapter 6 presents a procedure for optimizing allocation of vehicles in a free-floating carsharing operation, based on demand loads by zone and the cost of reallocation. Finally, Chapter 7 offers concluding remarks and describes opportunities for additional related work.

Chapter 2: Data Acquisition and Description

2.1 Partnership with Car2Go

The primary dataset used in this analysis was provided directly by Car2Go at no cost. The data is the result of an agreement between Car2Go and the researchers at the University of Texas, allowing the researchers to use the data and answer a variety of research questions in exchange for providing Car2Go with copies of all of the analysis results. Car2Go has no influence over the results of the analyses.

2.2 Data Setup

The data is in two sets; the first is a list of customers and the second is a description of vehicle usage. The customer database provides information on each of the 15,628 individuals who were Car2Go members as of January 9, 2011. While there is no personally identifying information included in the data, each member's information does include an address, city, and zip code, all as entered by the member. This data also includes a sign-up date provided by Car2Go.

The usage database has one record for each of the 161,963 rentals completed between November 23, 2009, and 6:48pm on January 9, 2011. The data includes the rental start date and time, rental end date and time, and the starting and ending locations. These locations are provided as both an address (the nearest street address to the final parked location of the vehicle) and a latitude/longitude. Rental duration is provided, calculated as the difference, in minutes, between the rental's starting and ending times. Finally, each record also includes the mileage traveled, to the nearest mile, during the course of the rental.

There is no indication of which member rented a vehicle; that is, there is no connection between the two sets of data.

2.3 Data Cleaning

Customer data had a number of questionable entries, as each piece of information is exactly as entered by the member. Some members were more precise in their data entry than others, using capital letters and avoiding typos. 291 members listed a PO Box (most of which, although not all, were within the Austin metropolitan area) as their home address, and these members were removed from the dataset. Car2Go members are from all over North America, from the East Coast to the West (including Vancouver, Canada). One member even listed a Surrey (England) home address. Because this analysis is focused on the Austin metropolitan area, members who listed a home address outside of central Texas were removed. Zip codes corresponding to the Austin metropolitan area (which includes Austin, Round Rock, Buda, Kyle, Cedar Park, Pflugerville, Westlake Hills, and Lakeway) were included if the zip code contained at least 50 members. This focus on Central Texas zip codes of at least 50 members resulted in a data set of 13,716 members (88% of total membership).

The usage data was much more consistent than the customer data, as it was all generated by computer and not subject to the same rates of human error. A very small percentage of the data showed obvious errors; for example, the duration of a rental was negative in two instances. However, removing these erroneous records had little effect on the overall data set of more than 160,000 records. Records outside of 2010 were also removed; in the analysis period of 2010 alone, 155,852 rentals were completed.

2.4 Exploratory Analysis

2.4.1 Customer Locations

While the vehicles rentals can only be started and ended within the geofenced area (32 square miles during the analysis year of 2010, although it expanded to 52 square miles in 2011), members reside throughout the Austin metropolitan area. Figure 2 shows the home locations of the members as black dots, with the red shaded area in the middle representing the geofence zone. 8,252 of the 15,628 members (53%) of all members live within the geofence boundaries.

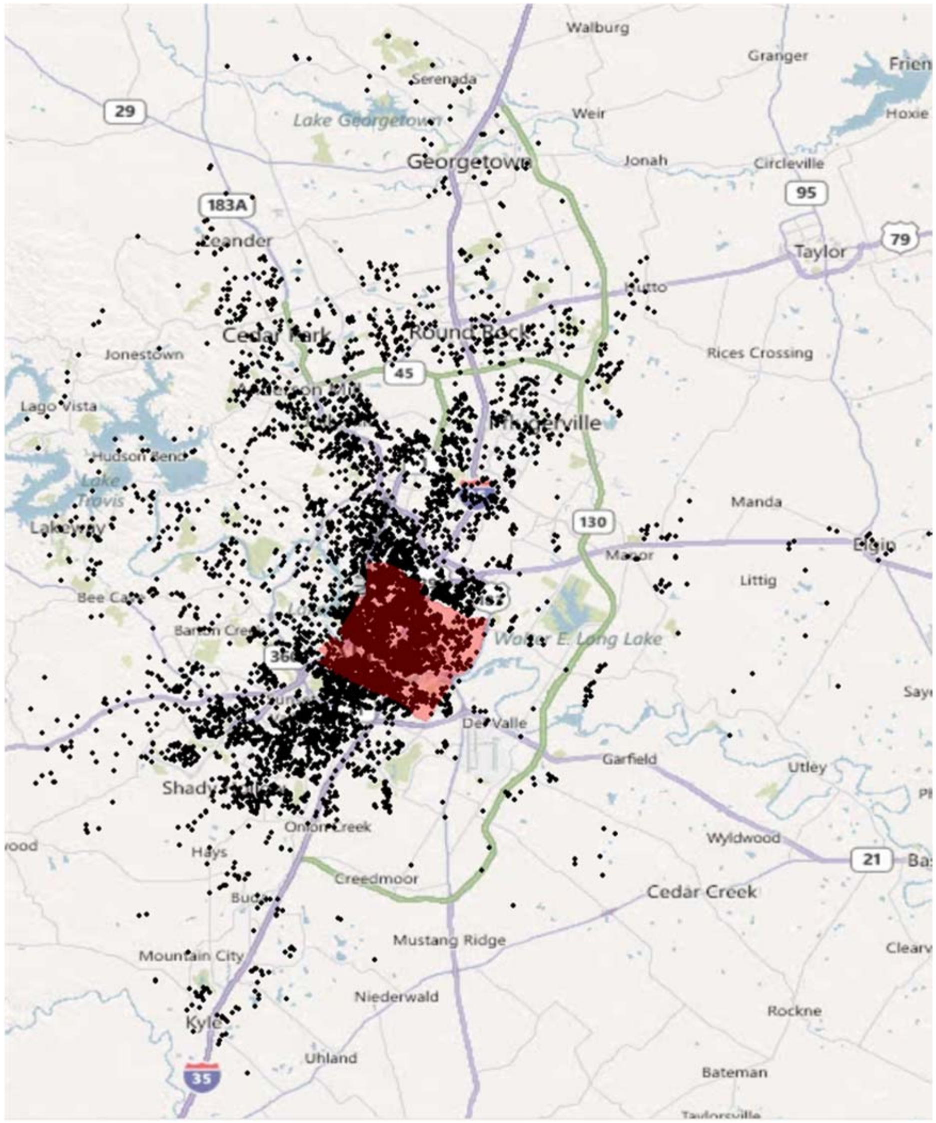

Figure 2: Car2Go Member Locations in Austin

Membership spatial patterns resemble general residential development in Austin: primarily north-south along the I-35 corridor but expanding to the northwest along the 183 corridor as well. The two zip codes with the largest percentage of all Car2Go members are 78705 and 78704. 78705, with 13.6% of all Austin-area members, are the West Campus and North Campus areas near the University of Texas. 78704, with 13.4% of all Austin-area members, is South Austin, bounded approximately by Lady Bird Lake to the north, I-35 to the east, Mopac to the west, and 290 to the south.

Other zip codes with large percentages of the total Austin-area Car2Go membership include 78703 (Enfield) with 8.9%, 78701 with 6.8% (downtown Austin), 78751 with 5.5% (the North Loop/Triangle area), and 78702 with 5.2% (East Austin). These six zip codes account for more than half (53.3%) of all Car2Go members (7,316 members) in the Austin area. Because more than half of all Car2Go members are in only six zip codes within central Austin, this region is clearly the core area for Car2Go's focus.

Downtown Austin (78701) has the largest percentage of residents who are members of Car2Go; 16.7% of all residents, or one in six residents, was a member of Car2Go at the end of 2010. The next highest density of membership occurs in 78705 (West and North Campus), with 5.8% of all residents a member of Car2Go. Car2Go has had remarkable success in market penetration in the downtown area. As nearly all of the residents of 78701 live in one of the several condo or apartment buildings that have risen in the central business district, it is likely that strong partnerships between Car2Go and these condo associations, in terms of reserved parking spaces and discounted memberships, have aided the penetration of Car2Go here. Based on the success of Car2Go with downtown residents, similar efforts may be possible with other dense developments throughout the central Austin area. Car2Go may consider looking into parking and membership arrangements with other large residential complexes in less dense zip codes, particularly in areas where parking is challenging.

Based on a Fall 2010 UT student population of 51,115 (2010-2011 Statistical Handbook, 2011) and a UT shuttle bus analysis of student residence locations, 58% of all residents in the 78705 (West/North Campus) zip code are UT students. Similarly, 9% of residents in 78741 (Riverside), 5% of 78731 (Far West), and 4% of 78703 (Enfield) residents are students. It would be difficult to definitively state that the 1,867 Car2Go members in this zip code are all (or even mostly) part of the 18,686 students in the zip code. However, it is very reasonable to assume that a large percentage of the members from 78705 are indeed students, considering that students do make up a sizeable majority of the zip code's total population.

Zip code 78745 (Sunset/Westgate) has the largest fraction of total Car2Go membership of any zip code outside of the geofence. 521 individuals, or 3.8% of total Car2Go membership, reside in 78745. 61 of these, or 11.7%, have indicated that they live in an apartment or a duplex.

78745 would seem to be a logical next expansion point for Car2Go, as it contains a significant percentage of total Car2Go members but is outside of the geofence and is therefore not part of the pickup/dropoff zone for the vehicles. Only 61 (11.7%) of these individuals report that they live in an apartment or a duplex (or any situation other than a single-family home); thus the majority of 78745 residents live in single-family homes and are still very interested in accessibility to alternative modes of transportation. Considering that 521 residents of the zip code (0.9% of all residents of 78745) are Car2Go members, usage would likely be fairly high here. When the geofence zone expanded in March of 2011, the zone approached, but did not encompass, this zip code.

Car2Go does have membership coming from many of the more outlying and less dense zip codes, including 78734 (Steiner Ranch/Lakeway), 78733 (West Bee Cave), and 78665 (Round Rock/Dell Diamond). However, the total number of members in each of these zip codes is well under 100, and the total membership penetration of the zip codes is very low. Many of these members may be individuals who live in these suburban zones but work in the core of Austin and choose to be a Car2Go member in order to have access to the vehicles during their work days. Because few of these far-suburban zip codes have strong transit access to central Austin, these individuals are almost certainly driving to work and thus have their own vehicles available to them throughout the day. Their Car2Go memberships may have resulted from curiosity or from a desire to drive a vehicle other than their own for errands throughout the day, perhaps because of parking challenges at their workplace.

2.4.2 Member Join Dates

As of January 9, 2011, Car2Go had 15,628 registered members. These registrations occurred in a very non-linear fashion throughout the year. By far, the day with the most registrations (405) was Friday, May 21, 2010, the day that Car2Go launched to the public. On that day, Car2Go hosted a party at a park in downtown Austin with live music and heavy publicity. Registration was also very high in the week leading up to the public launch; 753 members registered between Sunday, May 16, and Thursday, May 20. An additional 213 members registered on Saturday, May 22. The week of May 16 through May 22 accounted for the registration of 1,371 members, or 8.8% of total membership.

Car2Go offered free registration through Sunday, July 18, 2010. After this date, the cost of membership was $35, in addition to charges acquired while driving. July 18 accounted for 205 registrations, and 835 members registered during the week of July 12-18 (5.3% of total membership), when publicity about the upcoming membership fee was heavy.

Car2Go offered another free registration period during the month of October 2010. Registration was again high during this month, with 3,300 members (21.1% of total membership) registering between October 1 and October 31.

The average number of new registrations per day was approximately 37. However, because of the variation in registrations, with three noticeable spikes throughout the year (see Figure 3), the median number of new daily registrations was only 20.

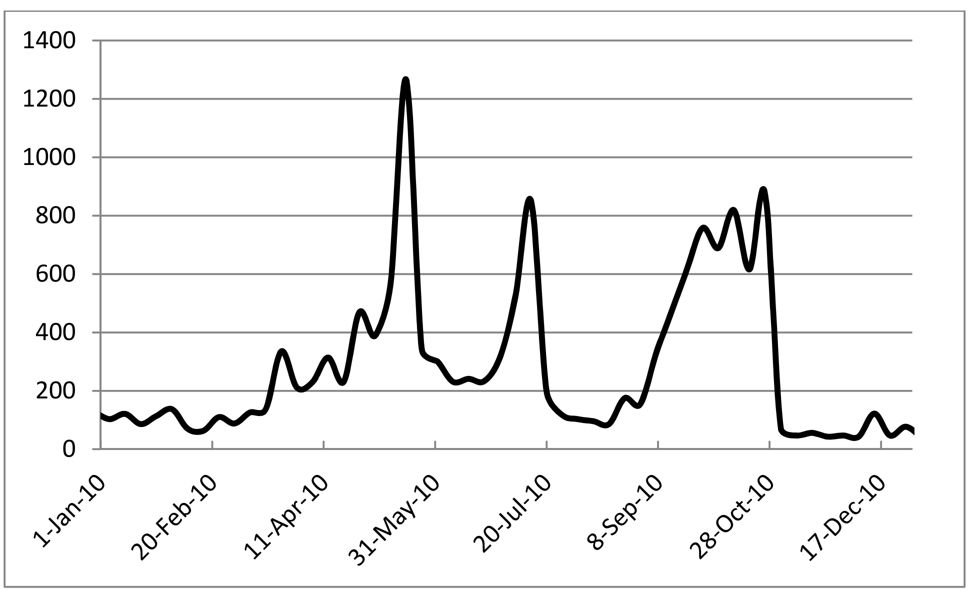

Figure 3: New Car2Go Members by Week

Promotions clearly have a very strong effect on the rate of new members joining Car2Go. More than 35% of members joined during only about 10% of 2010. Offers of free membership with a specific end date strongly encourage individuals to sign up for the service.

Membership in Car2Go does not necessarily mean that an individual makes use of the service regularly, or even at all. Because there are no links between the customer data and the usage data, it is impossible (using the provided data) to determine how many members joined during the promotional period only to never drive a vehicle at all. However, these non-users represent a very minimal cost to CarGo; if the cars are not being driven, they are not incurring costs for the company, and thus the only cost to Car2Go is the initial startup cost of driving history checks and membership cards.

Car2Go would likely be well-served by providing additional (but unpredictable) promotional periods throughout its tenure in Austin. Each of the promotional periods of 2010 resulted in significant membership increases, driven by members' desire to join before the end of a free period. Promotions encouraging potential members to join before an increase in cost may also show membership spikes, but these increases in registrations are not likely to be as pronounced as the upcoming end of a free membership period. Individuals will have a stronger preference for "$0 vs. $35" than they will for "$35 vs. $50" or some other increased membership rate. Thus, Car2Go may consider the possibility of having occasional weeks of free membership. Promotions may also include free driving time with membership, or other free amenities for new members. These promotional periods would need to be heavily advertised to be effective, as the three promotional periods of 2010 were.

2.4.3 Usage by Day of Week

During 2009, Car2Go rentals were primarily through the week. Of the 1,291 rentals between November 23, 2009, and December 31, 2009, only 31 (2.4%) were on Saturday and Sunday. Weekend rentals stayed low for the first several months of operation, with 4.5% of rentals on the weekend in January 2010, 6.3% in February 2010, 8.5% in March 2010, and 13.4% in April 2010. Before May 21, 2010, Car2Go's membership was made up primarily of City of Austin employees, who were permitted to use the vehicles on city business at no cost in exchange for the city receiving free dedicated on-street parking spaces. City employees were also provided personal memberships in addition to their employee memberships, but were required to pay for personal use of the vehicles. As a result, the vast majority (97.6%, initially) of trips were made during the weekday as the employees used the vehicles for free on city business. Cars tended to stay in one place during the weekend.

On May 21, 2010, Car2Go opened to the public and weekend rentals increased significantly. During the last third of May, after the public opening, 25.4% of rentals were on the weekend. Weekend rentals remained between 18.5% (June 2010) and 28.2% (October 2010) for the rest of the year. Friday rentals were exceptionally high in May 2010. 687 of May's 12,355 total rentals (5.6%) occurred on May 21, the public opening day.

As the carsharing program opened to the public, weekend trips increased to be equal in proportion to weekday trips. While trip purposes are not captured in the vehicle usage data, weekend use indicates that many members are choosing to use the vehicles for errands and social activities.

A very large number of rentals were made on the day of the grand opening to the public. Car2Go had positioned many of their vehicles around the park where the celebrations were being held and encouraged members and prospective members to test drive the vehicles. This level of activity is unmatched on any other day throughout the year. Most of these trips had no purpose other than "leisure/curiosity," so cannot be considered normal usage. Nonetheless, the usage levels of May 21 indicate that there was a great deal of interest in the program.

Trip purposes have clearly changed over the year of analysis. Initially, trips were almost exclusively made for business by city employees. However, personal use on the weekend increased as additional pilot groups joined the program and their members gained personal accounts in addition to the business accounts. Once the program opened to the public, weekend use increased significantly and stayed relatively high, with daily weekend use approximately equal to daily weekday use.

2.4.4 Usage by Hour of Day

During 2009, at the beginning of its operation, 84% of Car2Go's rentals were begun between the hours of 8am and 5pm. Only 2% of rentals began between 10pm and 6am. By June 2010, the first full month that the program was open to the public, 57% of the rentals began between 8am and 5pm and 13% began between 10pm and 6am. Across the first year of operation, the lowest hours of usage were consistently 4-6am.

The findings about changes in time-of-day usage correspond closely to the day-of-week usage findings. Initially, because members were primarily City of Austin employees and members of other pilot companies and organizations, most of the usage occurred during business hours. A nearly negligible percentage of rentals were during late-night hours. As public membership increased over the first eight months of operation, the proportion of use through the business day fell by more than a third and late-night usage increased almost sevenfold. These late-night rentals are almost certainly social in nature and represent individuals choosing to use Car2Go instead of transit (which generally has very limited service in the overnight hours), walking, or a personal vehicle.

If Car2Go is to undertake daily maintenance, cleaning, refueling, or relocation of the vehicles, they would be best served to accomplish these tasks during the hours of minimal usage between 4am and 6am. During this time, an average of about three vehicles were used each hour per day, leaving the vast majority of the fleet (approximately 197 vehicles) unused and available for maintenance, cleaning, refueling, and/or relocating. Attempting any of these tasks throughout the business day would inconvenience a significant number of members, as an average of at least 30 vehicles per hour were generally in use during the afternoon hours.

2.4.5 Distance and Time Traveled

Most trips made in Car2Go vehicles are relatively short in both time and distance, and have been since the program began. The median number of miles driven has remained steady at 2 since the program's opening, and the median number of minutes has ranged from 12 to 15. Even on the higher end of the spectrum, the 95th percentile for miles driven ranges from 18 to 24, depending on the month of analysis. The data's distribution does have a very long right tail, however; the maximum number of miles for one rental is 1,111 and the maximum rental length is 41,555 minutes (a little over 692 hours, or nearly 29 days).

Average and median rental lengths and distances consistently decreased over the analysis period. The mean number of miles driven in 2009 was 5.9, while in December 2010, this value had dropped to 5.1. Similarly, the mean length of a rental fell from 233 minutes in 2009 (the same time period in which the 29-day rental occurred) to 67 in January 2010 to 42 in December 2010.

The data indicate that members have become more efficient in their rentals. As the rental times and lengths decrease over the months, users are becoming more familiar with the system and more judicious with their use of the Car2Go vehicles. It is likely that members saw usage bills higher than they expected and adjusted their travel habits accordingly, using the vehicles only for the needed travel and releasing the rental while not physically in the vehicle.

City of Austin employees have changed their usage habits as well. Accustomed to using city fleet vehicles, which were under the control of the employee for the entire day, employees initially rented a Car2Go vehicle and did not end the rental until they had returned to city offices hours later. As the city urged the use of the vehicles for the trip only (not the stopover as well), employees became more likely to end their rental after they had driven to a destination instead of holding the vehicle until the end of the day or their return to the office. Over the months, city employees have become much more comfortable with the concept of walking away from the rental when reaching the destination and finding another vehicle for second and third legs of a trip (Forcier, 2011).

2.4.6 One-Way Rentals

In order to determine whether or not a rental was one-way, the latitude/longitude of both the starting location and ending location were used. After calculating the straight-line distance between the two points, sample observations were used to determine the practical distance corresponding to a numerical distance. Upon reviewing the data, it was determined that any rental ending within approximately two blocks of its origin point would be counted as a one-way rental. This straight-line distance worked out to a value of 0.005 (about 0.3 miles), calculated from latitude and longitude values.

Using this methodology, 44.1% of all rentals were one-way at the beginning of 2010. This percentage increased consistently throughout 2010 and reached 76.8% for the month of December 2010.

It is questionable, however, as to how many of these rentals are truly one-way. The user has the option to end the rental, proceed to shop, run errands, or otherwise fill his time, and then begin a second rental for the return leg of his journey (using either the same vehicle, if it is available, or another nearby available vehicle). Those who retained the vehicle through this series of events would show a much lower average speed throughout their rental period. Average rental speeds can be seen in Figure 4 below.

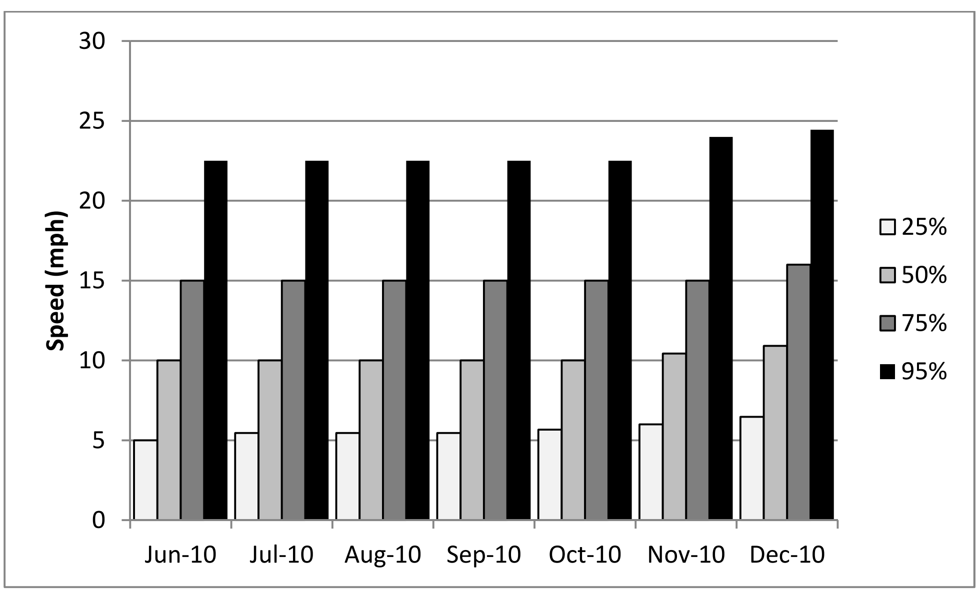

Figure 4: Average Rental Speeds, by Percentile

Figure 4 shows the average rental speeds for the 25th, 50th, 75th, and 95th percentiles of the data set for the period of June through December 2010 (the period in which the service was open to the public). The median speed were only about 10mph, reflecting both the urban driving situations and also the propensity for members to retain their rentals while out of the vehicle. 75th percentile speeds were decidedly higher, but still relatively low driving speeds, at approximately 15mph. Even 95th percentile speeds were only in the low 20mph range.

Figure 5 below shows a histogram of individual speeds by rental.

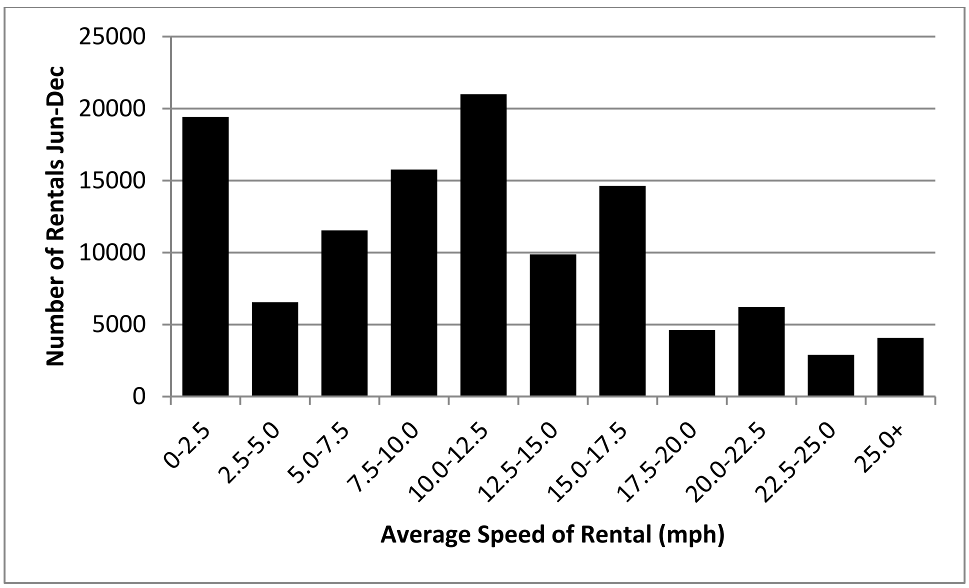

Figure 5: Rental Speeds for All Rentals, June through December 2010

Clearly, those rentals in the 0-2.5mph group encountered long period of stopping, likely because of leaving the vehicle while retaining the rental. The same may be true of the 2.5-5.0mph rentals, but those in the "speedier" groups (5+mph average rental speeds) are likely driving from one place to another, although perhaps driving in traffic or otherwise not taking the most efficient route.

Figure 6 considers driving speeds for only those rentals which were previously considered one-way (those ending more than two blocks or 0.3 miles from their origin).

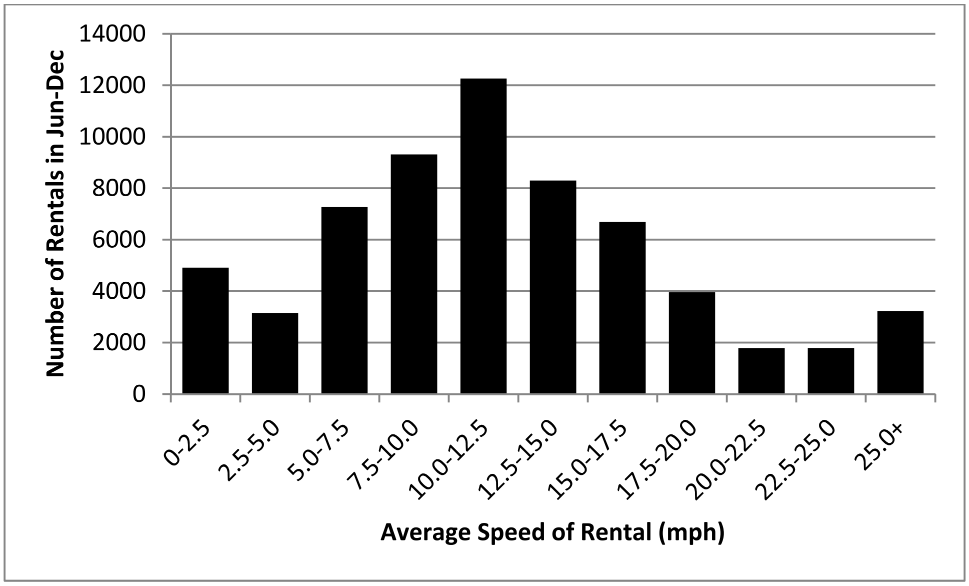

Figure 6: Rental Speeds for One-Way Trips, June through December 2010

Again, the 0-2.5mph rentals and the 2.5-5.0mph rentals are suspect in terms of continual driving throughout the rental, but the remaining trips can be considered true one-way trips. These rentals were driven at a moderate to reasonable speed from one place to another. 54,572 rentals between June and December 2010 fall into this category (of a total of 116,580 rentals made in the same timeframe), or 47%. On a monthly basis, the “5+mph and one-way” rentals ranged from a low of 44% in June 2010 to 51% in December 2010.

Regardless of the methodology used to identify them, one-way rentals have clearly increased in popularity since Car2Go opened its service to its first City of Austin employees. Initially, few of the rentals were one-way, indicating that most users were in the mindset of a traditional rental car or fleet car, in which the vehicle must be brought back to the place from where it was rented or borrowed. However, as time went on, members became more comfortable with the one-way feature and began to take advantage of the flexibility that these rentals offer.

2.4.7 Rental Locations and ParkSpots

A free-floating carsharing system is more economically challenging than traditional systems where the vehicle's locations are more controlled. In its operations to date, Car2Go has not built in subsidies for the additional vehicle movements required to keep the vehicles in areas of high demand. Its pilot project with the City of Austin consisted only of a straight trade of parking spaces (both designated Car2Go spaces and free use of metered and unmetered on-street parking) for free minutes for City of Austin employees' use. During the first year of operation, the 31 Car2Go designated spaces, which Car2Go calls ParkSpots, accounted for 14% of vehicle rentals. The most heavily used of these ParkSpots included the spaces outside of Car2Go's offices (4.2% of all 2010 rentals started or ended here), spaces at Trinity and 4th Streets (1.1% of 2010 rentals, and within one block of the downtown station of Austin's commuter rail line), and at Rio Grande and 23rd Streets (1.0% of 2010 rentals, in the center of the undergraduate housing district for the University of Texas). Car2Go does not share the length of time that vehicles are left in one place before being moved, but in informal conversations with management, initial plans were to move vehicles that had remained in place more than 48 hours. It is unknown at this time how many vehicles do require movement by Car2Go staff or how burdensome this is to the company.

Figure 7 shows the distribution of distances the vehicles are left from the nearest Car2Go ParkSpot. Approximately 40% of the rentals end either in a designated spot or within a quarter mile of such a spot. On the other end of the spectrum, 7% of rentals end at least three miles from the nearest ParkSpot. The majority of rentals do end in the vicinity of the ParkSpots, but this may be due more to the fact that the spots are located in areas of high density and travel demand than the actual presence of the dedicated parking spaces.

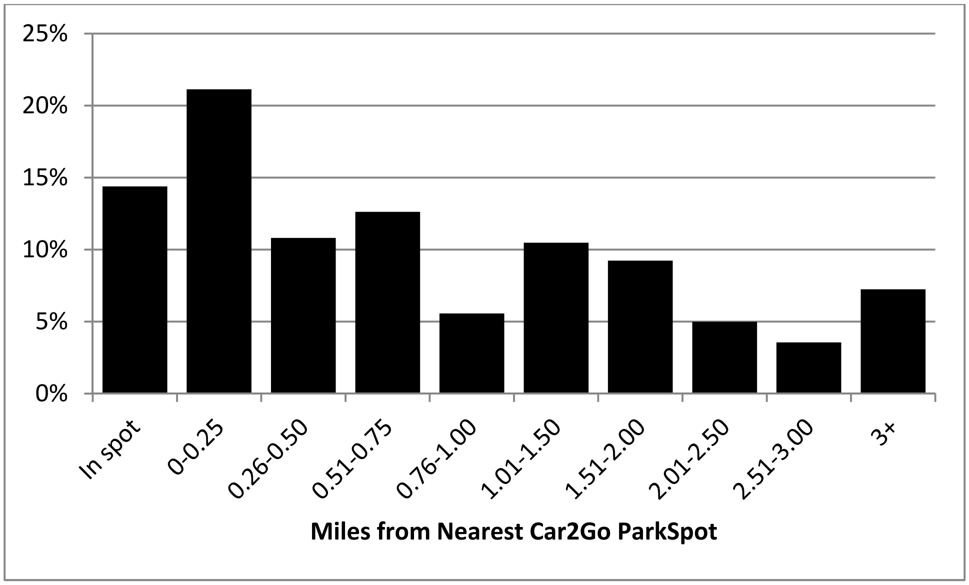

Figure 7: Rental Distances from ParkSpots

Chapter 3: Metropolitan Modeling

3.1 Carsharing in Metropolitan Areas

As of July 2008, most existing U.S. carshare organizations (61%) were nonprofits based in a single metropolitan area, including PhillyCarShare, San Francisco's City CarShare, and HOURCAR in Minneapolis and St. Paul. Austin was previously home to the non-profit Austin CarShare (ACS). Founded in 2006, this carshare organization managed a fleet of seven vehicles for a peak of about 450 members. However, as of July 2010, ACS ceased operations; representatives describe Car2Go's late 2009 entrance into Austin as "definitely a factor" (Gregor, 2010). Brandi Clark Burton, one of the founding board members of ACS, says "it was never a totally solid business model…it was always undercapitalized and held together by modest fundraising and the good will of board members" (Messer, 2010). After ACS closed, Car2Go offered free expedited memberships to former ACS members.

Carsharing programs, both non-profit and for-profit, have developed close relationships with universities around the country. The characteristics of these colleges vary widely, from large public institutions like the University of Michigan and Ohio State University, to smaller private universities such as the University of Pennsylvania and Cornell University. In combination, however, this segment of the market is one of the fastest-growing. College students are proving to be a successful demographic for carsharing organizations, and the parking challenges present at many universities further encourage students to consider carsharing instead of car ownership (e.g., "U. of Illinois", 2009). In fact, during the current decade, the university segment of the carshare market is expected to increase to 23% of the total market, from 4.6% in 2006 (Shaheen et al., 2006). However, many of these carsharing operations cater almost or completely exclusively to the university community and are not available to most residents of the city. These university-specific programs may consist of only a few vehicles parked on the campus, and membership is restricted to those affiliated with the university.

For-profit operations include ZipCar, the world's largest carsharing program with almost half of all carsharers worldwide ("The Connected Car," 2009), a total of more than 560,000 people (Rusli, 2011). ZipCar has locations in 35 states and the District of Columbia and has also developed relationships with more than 230 colleges and universities (Garthwaite, 2011). Zipcar's experience allows it to have a highly efficient operational side, with about $23,000 generated annually per car, and each employee supporting about 30 vehicles (Griffith, 2009). On April 14, 2011, Zipcar went public with a 56% gain on its first day of trading, putting its value above that of traditional vehicle rental companies (Brook, 2011), even though the company has not yet proven to be profitable. Zipcar's reported loss in 2010 was $14.7 million, and it has stated that it does not expect to turn a profit in 2011. Nonetheless, its sales rose 41.9% in 2010 to a total of $186.1 million (Rusli, 2011). Other carsharing operators have stated that Zipcar's strong IPO showing represents "credibility for carsharing as a viable business" (Garthwaite, 2011). Frost & Sullivan forecasts that revenue from all carsharing operators will increase from $253 million in 2009 to $3.3 billion by 2020 (Frost & Sullivan, 2010).

Other smaller for-profit nationwide organizations exist as well. For-profit operators make up only 29% of all carshare operators, but they account for 74% of all carshare members (Shaheen, 2008), largely due to the dominance of ZipCar. Traditional vehicle rental operators, including Enterprise, Hertz, and U-Haul, have also begun to offer hourly rentals and strategic placement of cars throughout cities, effectively acting as carshare organizations themselves (Jones, 2008; "WeCar", 2008; U Car Share, 2011).

The rate of taxation on carsharing operations in a variety of metropolitan areas has been found to be extremely high. A 2011 report by Depaul University's Chaddick Institute for Metropolitan Development found that "taxes on carsharing services substantially exceed those on other forms of consumer transportation including airline, bus, rail, waterway, and private automobile." These taxes are often at least twice the rate of sales taxes, if not much higher. This extremely high tax structure compared to taxes on privately owned vehicles "can be reasonably estimated to put 17,844 additional private vehicles on the road annually" (Bieszcsat & Schwieterman, 2011). Carsharing organizations in metropolitan areas (Boston, Chicago, and Portland, to date) that are making a concerted effort to reduce these taxes are expected to fare far better than those in metropolitan areas (including Miami, New York, Philadelphia, Pittsburgh, Seattle, and Tampa) with the highest tax rates. Perhaps unsurprisingly, tax-friendly cities have a large number of carshare operators; Boston, for example, has five (Zipcar, iCar, Mint Cars, HertzConnect, and RelayRide).

Carsharing is also branching out in the peer-to-peer direction in a few states and metropolitan areas. State Bill AB 1871 was passed by the California Assembly on June 3, 2010, creating a framework for individuals to allow the use of their own vehicles as a carsharing vehicle. While cars were certainly shared before the passage of this bill, AB 1871 clearly outlines liability issues. When a vehicle is being used as part of the carsharing program, the carsharing organization assumes all liability; the owner and his own insurance are liable whenever the vehicle is being used as a personal vehicle. Technology is used to determine which situation exists at any given time (Denning, 2010). The personal-car-sharing company behind the legislation is Spride, a Silicon Valley-based company that intends to link with San Francisco's City CarShare to pair people with vehicles. Other peer-to-peer carsharing companies include RelayRides in Boston, Getaround and JustShareIt in the San Francisco area, Go-Op in Pittsburgh, and Whipcar and Wombat Car Club in the UK.

All of these types of carshare operators are expanding throughout the country, and new programs are appearing regularly. In order to determine where the organization is most likely to be successful, this dissertation includes an analysis of cities that currently have at least one operational carsharing program serving the metropolitan area to determine characteristics that make cities amenable to successful programs.

3.2 Binary Logit Metropolitan Modeling

3.2.1 Model Estimation

This analysis considers North American cities only, as they have much more in common with one another than with European or Asian cities. Specifically, the analysis considers the 100 largest US cities (those with a population of at least approximately 200,000) and the twenty largest Canadian cities (those with a population of at least approximately 100,000). 40 of these 120 cities have at least one carsharing program operating in the metropolitan area, whether for-profit, non-profit, or peer-to-peer, or some combination of these. Free-floating carsharing programs currently exist in Austin, Vancouver, and San Diego, but this analysis is not limited to these programs. Cities which had a carsharing program only operating on a university campus were not considered to be carsharing cities.

A binomial logit model was used to test the likelihood of cities having any type of operational carsharing program, and the results are shown in Table 1 below. Table 2 shows summary statistics for each of the variables used in the model to allow for a better understanding of the parameter estimates.

Table 1: Binomial Logit Metropolitan Model Specifications

Variable	B-value	Sig.	Exp(B)
Constant	10.572	0.018	--
Percent of workers employed by any level of government	0.130	0.011	1.139
Average household size	-6.307	0.001	0.002
Percent of workers who commute via transit	0.160	0.000	1.174
Population of city (thousands)	0.00121	0.014	1.001
N=120 Nagelkerke R^2: 0.610 Percent Correctly Estimated: 83.3			

Table 2: Metropolitan Model Variable Summary

Variable	Min.	Max.	Mean	SD
Percent of workers employed by any level of government	7.4	33.3	16.4	5.6
Average household size	1.80	4.55	2.55	0.35
Percent of workers who commute via transit	0.2	52.8	8.4	9.5
Population of city (thousands)	78.1	8214.4	607.7	965.6

The larger the city, the more likely it is to have at least one active carsharing program. The significant exception is Houston, which has a population of more than five million but no carsharing services outside of very small and localized university programs. The mean population of cities with carsharing is approximately 939,000 (with New York City as the largest and Victoria, Canada, as the smallest), and the mean population of cities without carsharing is approximately 442,000.

Other findings are similar to those found in previous literature: as an increasing percentage of the city's commuters use transit, the city becomes more likely to have an active carsharing program. In this case, transit use represents a variety of characteristics of the city; increased transit use has long been shown to be highly correlated with residential density, employment density, and low levels of personal vehicle ownership and use (e.g., Frank and Pivo, 1994; Ewing et al., 2011). Increasing the average household size also reduces the likelihood that a city will have a carsharing program. Larger household sizes are often the result of increased family sizes, and particularly increased numbers of children. Research on carsharing programs has repeatedly found that the most likely users are those in relatively small households and those without children (e.g., Cervero et al., 2007; Grasset and Morency, 2010).

A new finding in this analysis is that the level of government employment in a city is a significant factor in its likelihood of having a carsharing program (significant at the 99% level). This may be because a large number of governmental agencies, from cities to states to federal departments, have partnered with carsharing to reduce their own vehicle fleet costs.

Many other variables were determined to be statistically insignificant. Population density and population growth trends were not significant, nor were age or gender distributions within the cities. Household income and per capita income have previously been found to be highly correlated with carsharing membership, but high incomes citywide were not a significant determinant of a city's likelihood of having carsharing. Student populations were not significant either, although if smaller university-specific carsharing programs had been included in the analysis, the results may have been different. Surprisingly, vehicle ownership statistics were not significant predictors of a city's carsharing probability; proportion of no-vehicle households and average number of vehicles per household were both found to be statistically insignificant.

3.2.2 Variable Correlations and Elasticities

Urban characteristics do not exist in a vacuum; correlations exist among these five variables, as shown in Table 3 below.

Table 3: Correlations among Metropolitan Model Variables (Correlation [Significance])

	Government Employment (%)	Household Size	Commuters Using Transit (%)	Population (in 1000s)
Government Employment (%)	1	-0.187 (0.041)	0.168 (0.066)	-0.085 (0.353)
Household Size	-0.187 (0.041)	1	-0.178 (0.052)	0.040 (0.667)
Commuters Using Transit (%)	0.168 (0.066)	-0.178 (0.052)	1	**0.480 (0.000)**
Population (in 1000s)	-0.085 (0.353)	0.040 (0.667)	**0.480 (0.000)**	1

The strongest correlations are between population and transit use rates (bolded in Table 3 above). This correlation is unsurprising; again with the notable exception of Houston, the largest cities in North America tend to have the most established and most extensive transit systems. Other correlations among the variables exist, but are low and often insignificant, indicating that the variables selected for the model are reasonably robust and independent.

Table 4 displays the effects of a 1% change in the mean of each variable on the probability of a city having at least one carsharing service. At the mean values for all five variables, the probability is 19.28%.

Table 4: Elasticities of Metropolitan Variables

	Pop.	Transit	HHSize	Govt	Prob (%)	% Diff.
Coeff.	0.001	0.160	-6.307	0.130	--	--
Mean	607.747	8.37	2.55	16.4	19.28	--
101%						
Pop	**613.824**	8.37	2.55	16.4	19.37	0.49
Transit	607.747	**8.45**	2.55	16.4	19.49	1.09
HHSize	607.747	8.37	**2.58**	16.4	16.90	-12.35
Govt	607.747	8.37	2.55	**16.6**	19.61	1.73
99%						
Pop	**601.670**	8.37	2.55	16.4	19.19	-0.49
Transit	607.747	**8.29**	2.55	16.4	19.07	-1.08
HHSize	607.747	8.37	**2.52**	16.4	21.91	13.63
Govt	607.747	8.37	2.55	**16.2**	18.95	-1.71

Household size has the highest elasticity of all of the explanatory variables. Increasing the size of the household by 1% from the mean (an increase of 0.03 people) decreases the likelihood of a city having carsharing to 16.90%, a decrease of 12.35%. Similarly, a 1% decrease in average household size results in a 13.63% increase in the probability of a city having carsharing (to 21.91%). Data was not directly available on the number of children per household, but increases in the average household size are likely due to an increasing number of children, which, as stated earlier, has often been associated with reduced carsharing membership.

Population has the lowest elasticity; a 1% increase (decrease) in population increases (decreases) the likelihood of a city having carsharing by 0.49%. Transit ridership among commuters has nearly a one-to-one relationship with likelihood of carsharing; government employment has slightly less than a two-to-one relationship, where increasing (decreasing) the proportion of residents employed by any level of government increases (decreases) the probability of carsharing in the city by 1.09% (1.08%).

This model could be used in combination with the membership prediction and allocation models presented later in this dissertation to determine how to best organize and equip any potential carsharing organization for any North American metropolitan area of at least moderate size.

Chapter 4: Membership Prediction

4.1 Literature Review

A great deal of existing literature looks at existing carshare members to determine the characteristics that these have in common. Given membership lists from a variety of programs around the United States, researchers have determined that those who have joined carshare programs tend to have a number of characteristics in common.

Low vehicle ownership is one of the most common characteristics of carshare members (Millard-Ball et al., 2005; Zhou et al., 2008). Celsor and Millard-Ball (2007) found that low vehicle ownership in a neighborhood has the strongest correlation with the level of carsharing service in the neighborhood. In San Francisco, City CarShare members were more likely to use the service heavily if they lived in zero-car households (Cervero et al., 2002); in fact, most City CarShare users do not own cars but substituted a carshare vehicle for a walking or bicycling trip (Cervero, 2002). Additionally, Steininger et al. (1996) found that more than half of European carshare members did not own a car prior to membership. More recently, Martin et al. (2010) reported that once a household joins a carsharing program, the average vehicle holding per household drops from 0.47 to 0.24; most of this drop is due to formerly one-vehicle households becoming carless.

Personal characteristics of individuals and households using carshare are also important. Members of carsharing organizations tend to be relatively young. Many researchers (Steininger et al., 1996; Cervero et al., 2002; Taylor, 2003; Brook, 2004; Lane, 2005) have found that a majority of members are in their late twenties to their early forties, with “thirty-somethings” being the most common users. Young adults today are less interested in vehicles than their older peers. The percentage of new cars sold to 21- to 34-year-olds reached a high of 38% in 1985, but is currently only 27%. This young generation typically reports higher interest in gadgets, such as cell phones and tablet computers, than in owning their own vehicle (Linn, 2010). Small household sizes also increase the likelihood of carsharing membership; Grasset and Morency (2010) compared average demographic values for Quebec as a whole to values for CommunAuto members to determine common member characteristics, finding that average household size is negatively associated with the probable market share of a carsharing station.

In most organizations, carshare members are highly educated, generally having earned at least a bachelor's degree (Shaheen & Rodier, 2005; Lane, 2005; Brook, 2004; Taylor, 2003; Steininger et al., 1996). These high levels of education often lead to higher professional employment (Shaheen & Rodier, 2005) and lower unemployment rates than the general population (Steininger et al., 1996). Correspondingly, studies have generally shown that typical carshare users have higher-than average incomes (Shaheen & Rodier, 2005; Millard-Ball et al., 2005; Taylor, 2003; Steininger et al., 1996). However, interest in carsharing is also present among those with lower-than-average incomes (Abraham, 1999; Taylor, 2003). These individuals may consider a private vehicle too expensive to purchase and maintain, but are still in need of a car for occasional driving trips.

Carshare users also tend to share important unquantifiable characteristics. Burkhardt and Millard-Ball (2006) found that carshare users tend to "be considered to be social activists, environmental protectors, innovators, economizers, or practical travelers," and Shaheen and Rodier (2005) have shown that typical CarLink (San Francisco) members exhibit "sensitivity to congestion, willingness to try new experiences, and environmental concern." Members often show "at least a vague interest" in environmental issues (Taylor, 2003). Generally, carshare users tend to be those who walk, bicycle, and use transit more than average members of their community (Loose et al., 2006).

Physical characteristics of a neighborhood have significant impacts on the level of support that carsharing receives. Celsor and Millard-Ball (2007) found that neighborhood and transit characteristics of an area are "more important indicators for carsharing success than the individual demographics of carsharing members." Increased household densities lead to increased use of carshare (Cervero & Tsai, 2004). Streets on which parking is limited or restricted show greater support for carsharing than streets that provide easy parking (Abraham, 1999). Another important predictor of carsharing usage is the distance to the nearest vehicle (Katzev, 2003); studies have shown that individuals are generally willing to walk up to 400m, but distances beyond this show a significant decline (Abraham, 1999).

Carsharing is not a concept that will appeal to the entire population of any metropolitan area, but certain subgroups have shown to be highly receptive to the idea. Generally, highly-educated and relatively young urban residents are the best prospects for a carsharing organization's members.

While there is clearly a significant amount of research analyzing the common characteristics of those who have become carshare members, little published research exists on membership prediction studies. Undoubtedly, research of this sort does exist, as few for-profit companies would begin operations without a sense of their likely success in a chosen market. However, much of this information is proprietary. This dissertation represents an initial academic attempt to predict membership from an entire metropolitan area's population.

4.2 Membership Prediction Modeling

This section of the dissertation attempts to answer the following two questions:

1. What census blocks are likely to contain any Car2Go members (one or more) and what blocks are likely to contain no members?
2. Of those blocks containing one or more members, what factors influence the proportion of the total population that is a member?

Because no information is provided about the individual members of Car2Go other than their address and join date, nothing is known about their individual characteristics, including age, gender, education level, income, etc. However, by comparing the addresses of registered members with Census 2010 information on the smallest possible level (in this case, the census block level, where total populations average less than 100), the user's characteristics can be approximated.

For analysis purposes, only census blocks that were both within the Austin metropolitan area and also within Travis County were considered. These blocks contained the majority of members (78%) and are the focus area of the Car2Go program. The other 22% of total members in 2010 had addresses outside of the Austin area, with residences from Dallas to England. Many of these members were likely temporary visitors to Austin who were curious about Car2Go during their stay. After eliminating blocks in the Austin metropolitan area with no population, a total of 8,111 census blocks remained, 3,136 (39%) of which contained at least one member.

Within the census blocks with at least one Car2Go member, a mean of 5.5% of the population is a Car2Go member; the median proportion is 2.8%. Six blocks had 100% of their population as members; these are blocks on the edge of the metropolitan area with very small populations – generally one household, of which the two or three household members are also Car2Go members.

Figure 8 and Figure 9 provide visual interpretations of the membership distribution. Figure 8 shows the extent of Travis County (in light gray) with the geofence zone as a dark gray area in the center. In terms of land area, the geofence zone accounts for 4% of the total area of Travis County. Figure 9 shows the census blocks within the geofence; dark blocks are those with at least one member and light blocks contain no members. (Many of these light blocks contain cemeteries, highway right-of-way, golf courses, medical centers, and other unpopulated areas.) There are 2,900 blocks within the geofence, 1,388 (48%) of which contain at least one member.

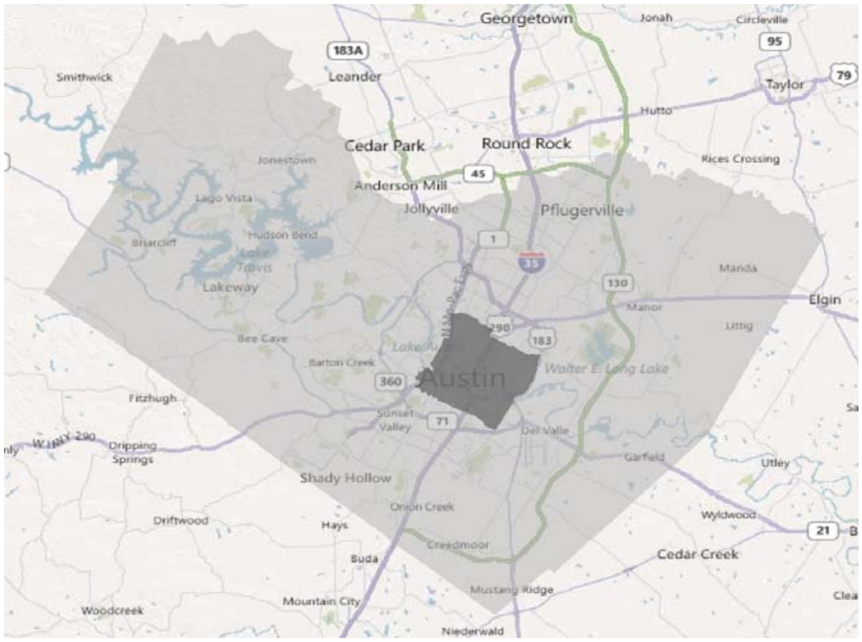

Figure 8: Map of Geofence within Travis County

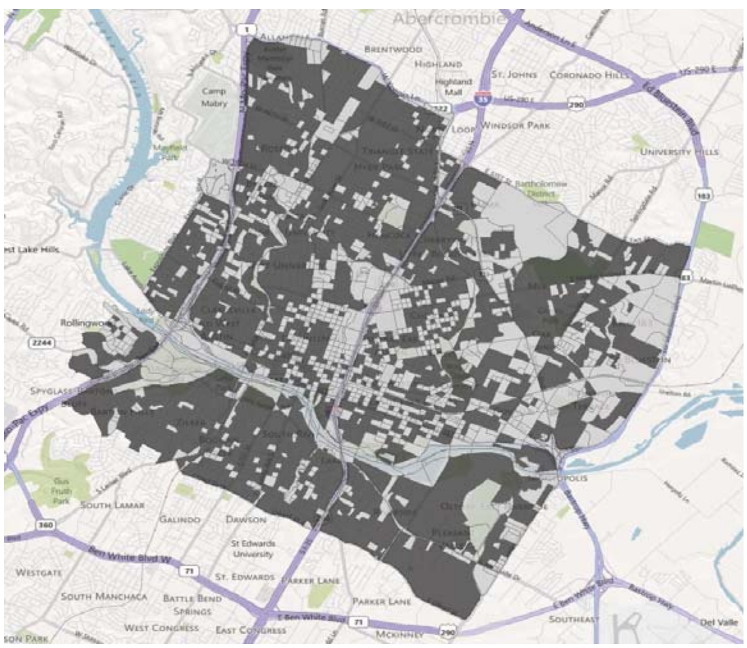

Figure 9: Map of Member Blocks within Geofence (dark represents membership)

In the following sections, three alternatives for calculating the membership proportion of any census block are outlined. The first alternative is two separate models: a binary logit to predict the presence of members, and a second linear regression to estimate the membership percentage among the population. The second alternative is also two separate models: the same binary logit and a logit model to estimate membership percentage. The third alternative is a Heckman sample selection model, which considers the two aspects of membership prediction (binary membership and then proportional membership) jointly. The Heckman choice is the most advanced modeling technique, but all three alternatives are described to allow a carsharing operation the greatest possible flexibility in choosing a prediction model for their use; if the organization is so inclined, they are welcome to use the first and second alternative's binary logit model as a stand-alone analysis.

A number of variables are 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
- 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

4.2.1 Two Prediction Models: Binary Logit and Linear or Logit Regression

One modeling technique to examine membership prediction is to separate the modeling into two models. First, consider a binary logit model to predict which census blocks will contain at least one member and which blocks will have no members. In the second model, limit the analysis to only those blocks with at least one member and use either linear or logit regression to estimate the percentage of the block's population that is a member.

In order to estimate the first (binary logit) model, variables likely to be significant were first added to the model; these included the geofence indicator and household size. Both did prove to be significant, and through a careful process of variable additions and eliminations, a set of five variables (plus a constant) were contained in the final first-stage model. Correlations among the variables were of particular consideration; for example, while the percent of the population between ages 20 and 39 and the percent of the population renting their home were both statistically significant, the two variables were very highly correlated (0.71), and thus the weaker of the two (renter proportion) was removed from the model. At the end of this process, a series of very statistically significant variables (Sig<0.000) remained.

Table 5 shows the specifications for this first stage model, and Table 6 provides summary statistics for each variable included in the model.

Table 5: Membership Prediction Model - Binary Logit

Variable	**B**	**Sig.**	**Exp(B)**
Constant	-0.300	0.012	--
Geofence indicator	0.941	0.000	2.563
Average household size	-0.365	0.000	0.695
Household density (per acre)	0.077	0.000	1.080
Percent of population aged 20-39	0.019	0.000	1.020
Percent of population working outside the home	-0.013	0.000	1.013
N=8,111 Pseudo R^2: 0.336 Percent predicted correctly: 70.2			

Dependent variable: Binary membership (Does the block contain at least one member?)

Table 6: Membership Prediction Binary Logit Summary Statistics

Variable	Min	Max	Mean	S.D.
Geofence indicator	0	1	0.26	0.44
Average household size	1.00	8.00	2.56	0.77
Household density (per acre)	0.00	30.91	3.08	2.53
Percent of population aged 20-39	0.0	98.8	33.0	18.5
Percent of population working outside the home	0.0	94.0	23.7	26.3

As is clear from the statistical significance of the constant in the above model specifications, the variables included in the model do not represent a complete description of the variability in the dependent variable (binary membership). This is the case with this model and also with other models described later in this section. All of the models developed here used socio-economic data readily available with the hope that these data would describe a large fraction of the dependent variable. In the binary logit model above, the pseudo R^2 value is 0.336, indicating that the included variables describe some, but not most, of the variability in the dependent variable.

To hypothesize on variables that may be significant but are not included in the model would reduce the value of the work done here and in the following sections of the dissertation. A user of these models would then need to acquire additional hard-to-find variables, many of which may not be generalized but instead location-specific. Market research to predict carsharing membership or other relevant information may use stated preference surveys, which, when done properly, could provide higher-resolution information than widely-available census data. However, these models are intended to operate in the public domain, allowing metropolitan planning organizations and other public agencies to evaluate carsharing; these organizations are not likely to have either the manpower or financial resources to create and distribute stated preference surveys. The models included in this dissertation can be used as a screening tool to determine general operating parameters for a carsharing organization, even though additional variables may be lacking.

Given these limitations, the variable with the most impact on the likelihood of a census block containing at least one member is the indicator variable for whether or not the block falls within the geofence. The odds ratio (calculated as $\exp(B_{\text{Geofence indicator}})$)

associated with this variable is approximately 2.6, indicating that a census block within the geofence is 2.6 times more likely to contain a member than a block outside the geofence. Considering that 78% of all members do reside within the geofence, this is unsurprising.

The average household size of all households within the block is also a key predictor; an increase of one additional person in the average household reduces the likelihood of the block containing any members by more than 30% (the odds ratio is 0.695, indicating that one additional household member results in a membership likelihood that is 69.5% of a household without the additional member). As discussed in the metropolitan modeling section (Chapter 3), increases in household size are often closely connected to increases in the number of children. In this particular data set, the correlation coefficient between average household size per census block and average number of children per household (per census block) is 0.85, confirming the close relationship between the two values.

Household density per acre, percent of population between ages 20 and 39, and percent of workers who work at home all have much smaller odds ratios than the geofence indicator and household size, but the units on these three variables are much different. Household density has the expected positive effect on the likelihood of a census block containing a member; increased household densities are likely representative of general land use characteristics, with increased densities linked to increased mixed land uses as well as proximity of carsharing vehicles to larger numbers of members.

The correlations between these five variables are shown in Table 7. The existing correlations are generally unsurprising.

Table 7: Membership Prediction Binary Logit Variable Correlations

	Geofence	HH Size	HH Density	Percent 20-39	Work Outside Home
Geofence	1	-0.283	0.336	0.379	-0.323
HH Size	-0.283	1	-0.284	-0.403	0.169
HH Density	0.336	-0.284	1	0.472	-0.171
Percent 20-39	0.379	-0.403	0.472	1	-0.169
Work Outside Home	-0.323	0.169	-0.171	-0.169	1

*All correlations are statistically significant at the 0.01 level.

Table 8 shows elasticities of the variables included in this first stage model, calculated by increasing each of the variables. The geofence indicator variable was changed from 0 to 1, as increasing a binary variable by 1% has no meaning. Household size, an ordinal variable, was increased by one, and the remaining variables were increased by one percent. For reference, at median values, the probability of a census block containing at least one member is 36.5%. Using these standardized considerations of the variables, it is clear that the household size has a very high elasticity compared to the other variables included in this model; an increase of one person in the household (to 3.5 from the median of 2.5) decreases the likelihood of a block containing a member by nearly 29%. On the other hand, the percent of those working outside the home has the lowest elasticity, as a one percent increase in the proportion of a block's residents working outside the home only decreases its likelihood of containing a member by 0.1%. For the geofence indicator variable, including a census block in the geofence increases the likelihood that it will contain a member by more than 63%.

Table 8: Membership Prediction Variable Elasticities

	Geofence	HH Size	HH Density	20-39	Work Outside
Coefficient	0.941	-0.365	0.077	0.019	-0.013
Median	0	2.50	3.08	31.4	13.3
Probability (% change) at 101% of Median*	59.6 (63.1)	28.6 (-21.8)	36.6 (0.2)	36.7 (0.4)	36.5 (-0.1)

*Geofence indicator variable was changed from 0 to 1 instead of increased by 1% because increasing a binary variable by 1% has no practical meaning. Household size, an ordinal variable, was increased by one.

The literature on carsharing members has long found that those in their twenties and thirties are most likely to be members of the service, as discussed earlier, and this model confirms these findings in the Austin area. A mean of 33% of the population of all census blocks falls within this age group; considering only those blocks within the geofence, the mean value rises to 44%.

Those who work at home are another market for carsharing, a new finding in this analysis. While the effects of increased percentages of census block residents working at home are slight, they are nonetheless statistically significant. Those who do not work outside the home clearly do not need to own a personal vehicle for commuting, and vehicle ownership has been found to be slightly lower among this group (Beckman and Goulias, 2008). In addition, working at home may allow for more flexible scheduling, allowing the workers to run errands and make other trips throughout the day, not only at the lunch peak as is the case with more traditionally-located employees.

The second step of the first two-step methodology is a linear regression model to estimate the percentage of members in census blocks with at least one member. The model specifications are shown in Table 9.

Table 9: Second-Stage Membership Prediction Model - Linear Regression

Variable	Coeff.	Std.Err.	Sig.
Constant	1.757	0.335	0.000
Geofence indicator	5.407	0.327	0.000
Percent of population aged 20-39	0.032	0.008	0.000
N=3,306 Adjusted R^2: 0.106			

*Dependent variable: percentage of the population that is a member.

This linear regression model is only applicable for those blocks with at least one member, as predicted with the first-stage binomial logit model. Once a block is predicted to have at least one member, only two variables are needed to estimate the percentage of the total population of the block that is a member: a geofence indicator variable and the percent of the population between ages 20 and 39.

Because this is a linear regression model, interpretation of its coefficients is straightforward. Beyond the constant of 1.8%, blocks within the geofence are estimated to have 5.4% of the population as carshare members, with an additional 0.03% for each percent of the population falling between the ages of 20 and 39. The mean proportion of "twenty and thirty-somethings" within the geofence is 44%, while outside the geofence it is only 29%. This model is very simple; carsharing organizations planning their operating characteristics can easily determine the locations of "twenty and thirty-somethings" from census data, and the operational boundaries are determined by the organization itself.

A second option for the second-stage membership prediction is a logit model. Logit models are well-suited to data in which dependent variables range from zero to one, as the proportion of the population does in this case. Using the same data set, Table 10 shows the logit model specifications.

Table 10: Second-Stage Membership Prediction Model - Logit

Variable	Coeff.	Std.Err.	Sig.
Constant	-2.356	0.034	0.000
Geofence indicator	1.015	0.018	0.000
Household size	-0.492	0.013	0.000
			N=3,306
			Adjusted R^2: 0.373

*Dependent variable: percentage of the population that is a member.

The logit model is similar to the linear regression model in its simplicity and robustness, although the two models do not use the same set of variables. Location within the geofence is of great importance to both models, but while the linear regression model also considered the percent of the population aged 20-39, this logit model instead uses the household size as a key variable. Increasing the average size of the households in a census block reduces the estimated proportion of the block's residents who are carshare members.

Using the stage one binary logit model and either of the second-stage models in combination with the metropolitan modeling of Chapter 3, any organizations contemplating carsharing can choose their operating areas and target members with reasonable certainty.

4.2.2 One Prediction Model: Heckman Sample Selection Model

Another option for predicting membership is the use of a Heckman (1979) sample selection model. This model considers correlation in unobserved factors in both the binary membership determinant and the proportion of members and uses a correction factor as a regressor in the proportion model after estimating the binary membership model parameter estimates. It provides an analysis that is more of a joint model than the previous methodologies, allowing the errors in the prediction of the two dependent variables (binary membership and continuous membership proportions) to be connected. This technique is appropriate to model the membership proportions when more than half of all census blocks contain no members.

Heckman's procedure uses the logit results to generate an inverse Mills' ratio in the first stage; this ratio is then included in the second-stage OLS modeling to control for selectivity bias.

If a random sample of I observations is considered, then equations for individual i are $Y_{1i} = X_{1i}\beta_1 + U_{1i}$ and $Y_{2i} = X_{2i}\beta_2 + U_{2i}$, and $E\left(U_{ji}\right) = 0$. The joint density of U_{1i}, U_{2i} is $h(U_{1i}, U_{2i})$. Assuming that $h(U_{1i}, U_{2i})$ is a bivariate normal density,

$$E(U_{1i}|U_{2i} \geq -X_{2i}\beta_2) = \frac{\sigma_{12}}{(\sigma_{22})^{\frac{1}{2}}}\lambda_i$$

where

$$\lambda_i = \frac{\phi(Z_i)}{1 - \phi(Z_i)} = \frac{\phi(Z_i)}{\phi(-Z_i)}$$

where φ and Φ are, respectively, the density and distribution function for a standard normal variable, λ_i is the inverse of the Mill's ratio, and

$$Z_i = -\frac{X_{1i}\beta_1}{(\sigma_{11})^{\frac{1}{2}}}.$$

Knowing Zi and hence λ_i, λ_i can be entered as a regressor in the OLS equation. The results of the Heckman's sample selection modeling are shown in Table 11 below.

Table 11: Heckman Sample Selection Model

		B	Sig.	Exp(B)
Step One: Binary Membership	Constant	-0.717	0.000	--
	Geofence indicator	1.523	0.000	4.586
	Average household size	-0.228	0.000	0.796
	Work outside home (%)	-0.032	0.000	0.969
	White/non-Hispanic (%)	0.019	0.000	1.019
	Commuters using transit (%)	0.041	0.000	1.042
Step Two: Proportional Membership	Constant	5.217	0.000	--
	Ages 20-39 (%)	0.049	0.000	--
	Lambda	-2.820	0.000	--
Total Observations = 8,111 Censored Observations = 4,805 Pseudo R^2 = 0.092				

Note: The discrete response in this model is whether at least one member exists in the Census block, and the continuous value is the share of adults in the block that are members.

The results of this membership prediction methodology are similar to those of the previous methodologies, but a few differences have appeared.

The most dramatic difference is the importance of being located within the geofence. As compared to the first stage binary logit modeling, the geofence indicator's importance has increased; the likelihood of a census block within the geofence containing carshare members is approximately 4.6 times the likelihood of a block outside of the fence; this compares to a ratio of 2.6 under the previous methodology.

Average household size has a negative impact on the likelihood of carshare members, as expected and as found previously. One additional person, on average, per household results in the census block being only about 80% as likely to have carshare members; this compares to 70% likelihood with one additional person in the stand-alone binary logit model of the previous methodology.

The fraction of the population working outside the home also has a similarly negative effect on the likelihood of carsharing members in a census block. One additional percent of the population working outside the home decreases the likelihood of carshare members by approximately 4%, as compared to just over 1% in the previous methodology.

Two new variables have shown to be statistically significant in the first stage of the Heckman sample selection model: transit use among commuters and proportion of the population that is White/Non-Hispanic. Neither of these variables was significant in the stand-alone binary logit model. The proportion of White/Non-Hispanics living in a census block has a small, but statistically significant, positive effect; one additional percentage of the population describing themselves as white increases the likelihood of carsharing members by approximately 2%. Increasing the proportion of commuters who use transit also has a slight but statistically significant increase in the likelihood of members, with a 4% increase in likelihood increasing from a 1% increase in transit commuters.

In the second stage of the Heckman sample selection model, the results are more simplistic than those of either the linear regression or the logit models of the previous methodology: the percentage of those aged 20-39 is the key predictor of the proportion of the population that will be a carshare member. A 1% increase in the population of "twenty and thirty-somethings" in a census block increases the member proportion of the population by 0.05%. As before, it is important to note that the mean proportion for this age group is 33% overall, 44% within the geofence, and 29% outside of the geofence.

In order to better understand the meaning of these variables, it is also important to calculate their elasticities. For the first stage of the joint model, at median values, the likelihood of a census block containing a carshare member is 39.61%.

Table 12 describes the effect of changing the independent variables on this likelihood.

Table 12: Heckman Sample Selection Stage One Elasticities

Variable	Change	New Likelihood	Percent Change in Likelihood
Geofence indicator	0 to 1	75.0%	89.5%
Household size	Increase by one	34.3%	-13.4%
% Work outside home	Increase 10%	38.6%	-2.6%
% White/Non-Hispanic	Increase 10%	42.6%	7.5%
% Commuters using transit	Increase 10%	39.8%	0.4%

As is the case in many of the models considered in this dissertation, the geofence indicator variable has the strongest effect on carsharing membership (and, as will be shown later, use). Increasing the average household size by one individual decreases the likelihood of members in the block by 13%. Transit commuting has the lowest effect on member likelihoods; increasing the percentage of commuters 10% only increases the likelihood of the block containing a member by 0.4%. As a result, while the variable is statistically significant, its practical significance is low and both carsharing organizations and metropolitan planning agencies may want to consider not including this variable in their analyses.

The total proportion of the population that can be expected to be a carsharing member can be calculated by multiplying the two percentage values together. Combining the likelihood that a census block will contain any members with the expected proportion of members in "member blocks" will provide an estimate of the total proportion of the population that is a carsharing member. Because of the correction factor lambda that is present in the second stage of the Heckman sample selection model, the probabilities can be considered independent, which is not the case in the previous two sets of separate models. Table 13 describes these total expected proportions and their change as each independent variable is adjusted. The geofence indicator has the greatest elasticity, alerting a carsharing organization that their operational boundaries are the greatest single factor in determining the total proportion of a metropolitan population that is likely to become a carsharing member.

Table 13: Heckman Sample Selection Joint Elasticities

Variable Changed	Type of Change	New Total Membership Proportion	Percent Change in Proportion
No change – median values	None	1.56%	--
Geofence indicator	0 to 1	2.95%	89.5%
Household size	Increase by one	1.35%	-13.4%
% Work outside home	Increase 10%	1.52%	-2.6%
% White/Non-Hispanic	Increase 10%	1.68%	7.5%
% Commuters using transit	Increase 10%	1.56%	0.4%
% Ages 20-39	Increase 10%	1.62%	3.9%

4.2.3 Membership Prediction Model Recommendation

This chapter has provided three separate options for predicting membership in a carsharing program given metropolitan demographics: (1) a binary logit model to identify census blocks with any members, followed by a linear regression model to estimate the percentage of population that is a member in blocks expected to contain members; (2) the same binary logit model to identify census blocks with any members, followed by a logit model to estimate the membership percentage; and (3) a Heckman sample selection model to jointly estimate blocks with members and membership percentages in blocks with members. While all of these options are valid methods to predict carsharing membership, the strongest option is the Heckman sample selection model. Because it allows the errors in the two prediction steps to be correlated, this methodology provides the soundest estimate of predicted membership.

Chapter 5: Mode Share Modeling

5.1 Mode Share 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).

One mode of transportation that currently has a low mode share but has nonetheless received a great deal of attention is bicycling. Considering the characteristics of demographics and the environment that influence bicycle mode share may provide insight into carsharing, another alternative transportation mode with a low mode share. Bicycle facilities, including bicycle parking, are key to increasing bike shares (Schneider, 2011; Krizek et al., 2009; Cleaveland and Douma, 2009; Hunt and Abraham, 2007). Low car ownership, proportion of bicycle routes that are separated from motorized traffic, relative flatness of the terrain, and temperate climates all increase the proportion of those who bicycle to work (Heinen et al., 2010; Parkin et al., 2008; Winters et al., 2007; Baltes, 1996). The social environment of a workplace also factors into a commuter's decision to bike (Handy and Xing, 2011). Parkin et al. (2008) suggest a 43% saturation level for bicycle use, much higher than can be expected for carsharing.

The analysis of pedestrian mode share is similar to that for bicycling, but there are some distinct differences. The spatial attributes of a region (including local road network and job densities) are major factors in determining the proportion of walking trips, much more so than for any other travel mode (Sanni and Abrantes, 2010; Goetzke and Andrade, 2010). Tree canopy coverage, sidewalk availability, and low perceived crime rates encourage individuals to walk (Schneider, 2011; Rodriguez and Joo, 2004). Social and recreational trips, particularly those occurring on weekends, increase the likelihood of an individual choosing to walk (Cervero and Duncan, 2003), as does the prevalence of mixed-use land development (Rajamani et al., 2003). As with bicycling, the social attributes of the household and neighborhood have a strong influence on the likelihood of walking (Goetzke and Andrade, 2010; Schneider, 2011).

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 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.

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). Many of these trips are concentrated in evenings and weekends (Hope, 2001), resulting in reduced vehicle availability at those times. In areas with limited personal vehicle availability, the primary use of carsharing is local residential and neighborhood use (Barth et al., 2006). Longer membership durations generally lead to more frequent use of shared cars (Katzev, 2003).

5.2 Mode Share Analysis

Because there is little previous research on mode splits for carsharing of any type, free-floating or not, this dissertation considers a variety of 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 Metropolitan Planning Organization (CAMPO). The second method considers only trips that were "true trips," one-way trips that contained 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. Summing all three of these 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. Earlier exploratory analysis confirmed 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 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.

5.2.1 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 to 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.

Before attempting to create a mode share model, it is reasonable to examine the data in the form of scatter plots to determine the viability of including certain variables in the final model. If these scatter plots show noticeable patterns in the data, the model is likely to be robust.

Figure 10 shows the relationship between total density (the sum of household density and employment density, both on a per acre basis) and mode share for all rentals. There is a noticeable negative trend in the scatter plot; as the mode share increases, the density tends to decrease, and vice versa. This is an unexpected relationship, as increased land use densities generally have been found to result in increased membership levels. However, as there is little available research on carsharing mode split analysis, there is no basis for believing that increased carsharing mode shares may be directly related to land use densities. It may be that areas of increased density have such an increased frequency of trips of all kinds (including transit, walking, and bicycling) that the increased numbers of carshare trips is a relatively lower increase compared to the increase of trips of other types. This would result in a smaller mode share even though the absolute number of carsharing trips would be higher than in less dense zones.

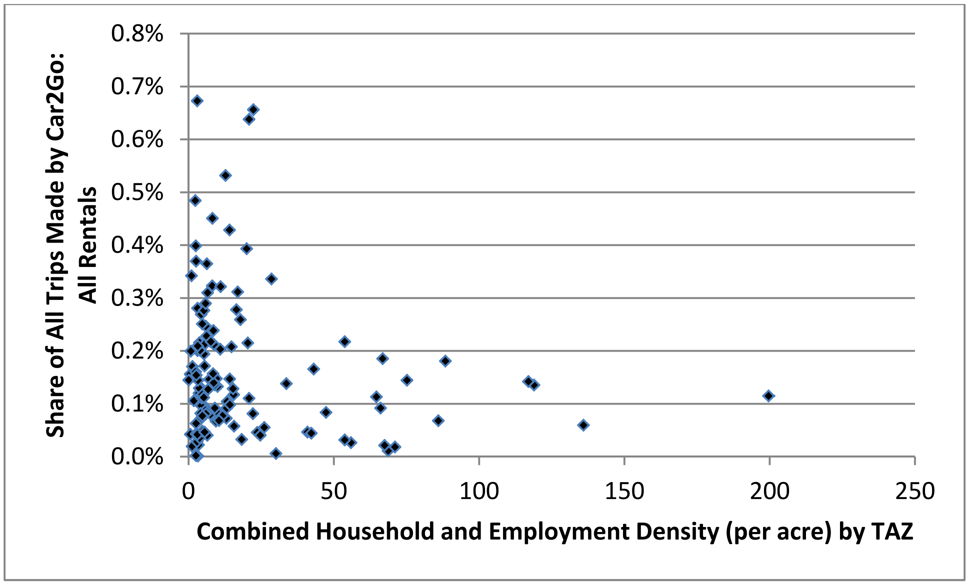

Figure 10: Car2Go Mode Share (All Rentals) vs. Density

In order to obtain a closer look at the scatter plot for the lower densities, which are closely plotted and thus difficult to see in Figure 10, Figure 11 shows the same plot but only densities between 0 and 100 homes/jobs per acre. Here, the negative trend is still visible, and the large clusters of points with low densities and low mode share are clearer.

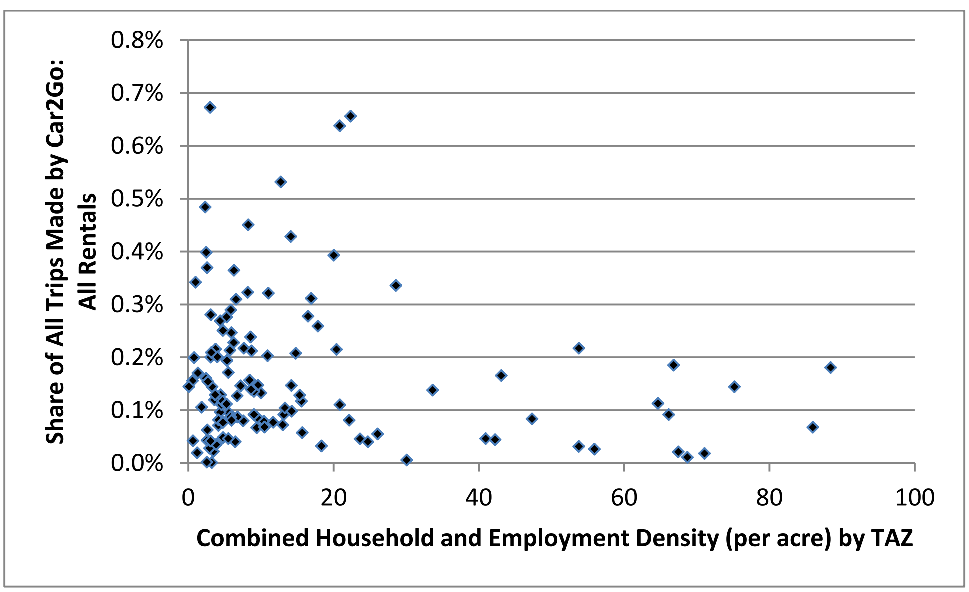

Figure 11: Car2Go Mode Share (All Rentals) vs. Density - Zoom

Figure 12 shows a scatter plot of the share of all Car2Go rentals as compared to the average household size in a TAZ. Again, a noticeable negative relationship appears – increased mode share correlates to reduced average household size, and vice versa. Based on previous studies, this result is expected; increased household sizes have been found to be connected to decreased carsharing membership, so it is logical that they would also be connected to decreasing carshare mode shares.

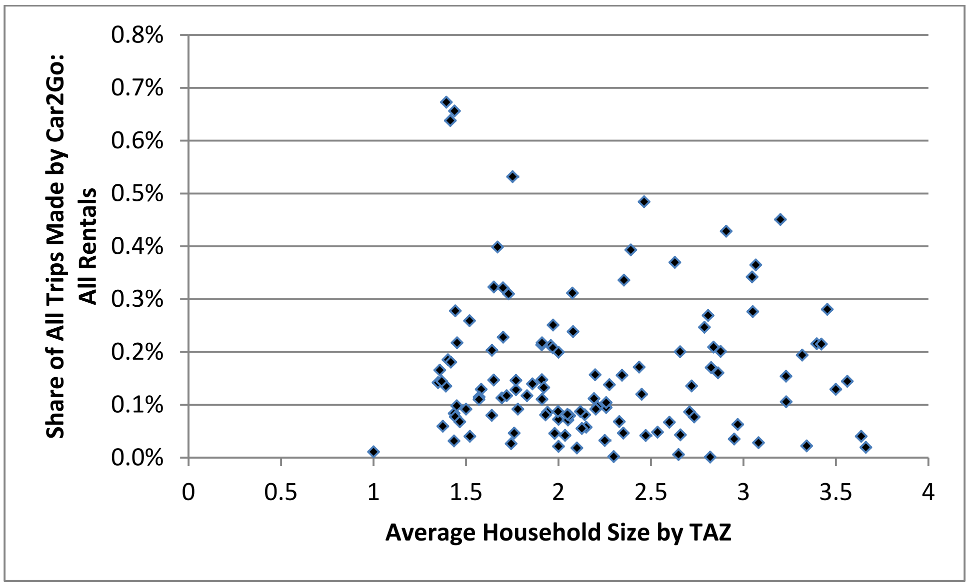

Figure 12: Car2Go Mode Share (All Rentals) vs. Household Size

Figure 13 shows the relationship between the Car2Go mode share and the median household income in each TAZ. Increased mode share tends to be correlated with lower household incomes, indicating that those with the highest incomes are less interested in using carsharing, likely preferring their own personal vehicles. As with land use densities, this is an unexpected result, considering that most previous research has found that carshare members tend to have higher-than-average incomes. However, membership and mode share are two separate analyses, and there may not be as straightforward a connection between mode share and income as there is between membership and income. After all, the previous chapter's membership prediction modeling did not find a statistical significance to income when predicting which residents of a metropolitan area are likely to become members. Income may be more pronounced when considering the attributes of those who have already become members than when predicting future membership from the population at large.

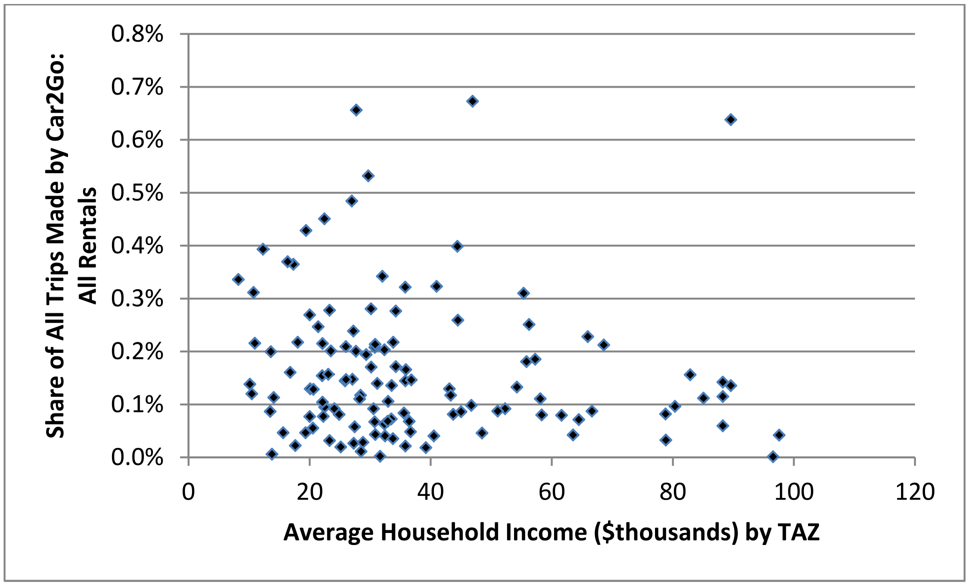

Figure 13: Car2Go Mode Share (All Rentals) vs. Income

Interestingly, low mode shares are prevalent across the entire range of income levels. Previous research has found that individuals with higher incomes are more likely to carshare than those with low incomes, but this may not hold true when considering zones instead of individuals or households.

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 reduced the amount of heteroskedasticity in the data; as seen in the above scatter plots, the variability does fluctuate quite a bit across the range of the variables. The log(y) transformed variables can be seen in Figure 14, Figure 15, and Figure 16; the heteroskedasticity has clearly been reduced.

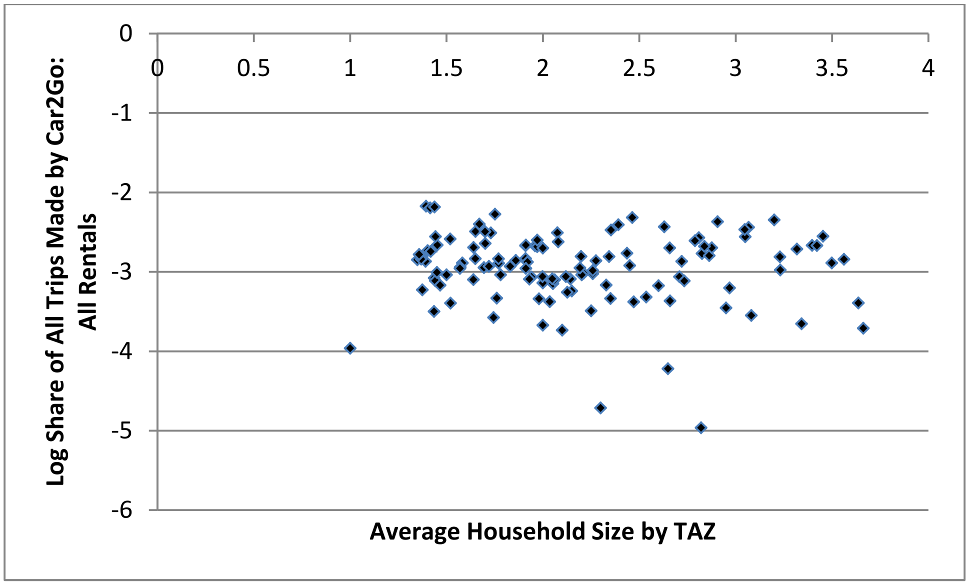

Figure 14: Log Car2Go Mode Share (All Rentals) vs Household Size

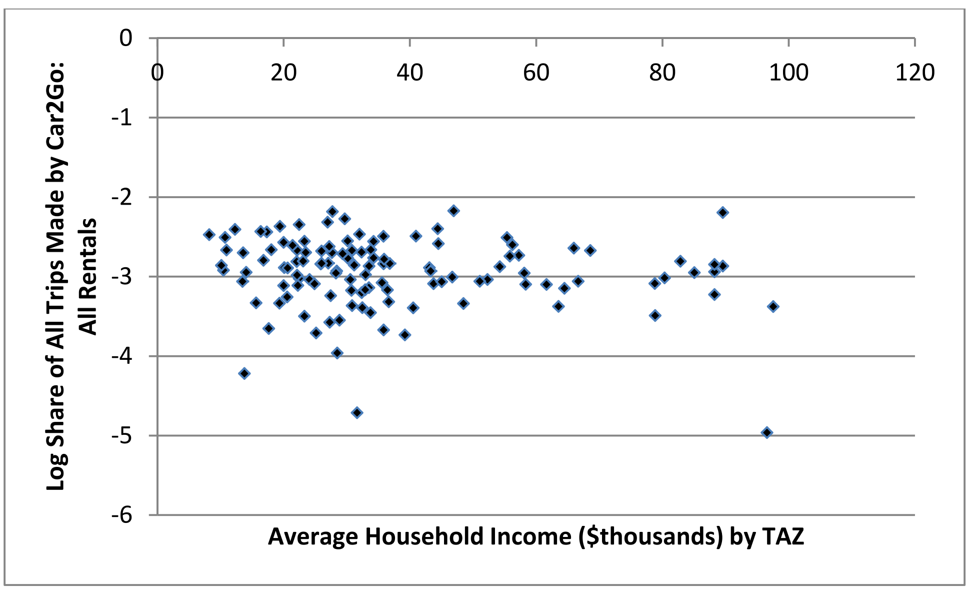

Figure 15: Log Car2Go Mode Share (All Rentals) vs. Income

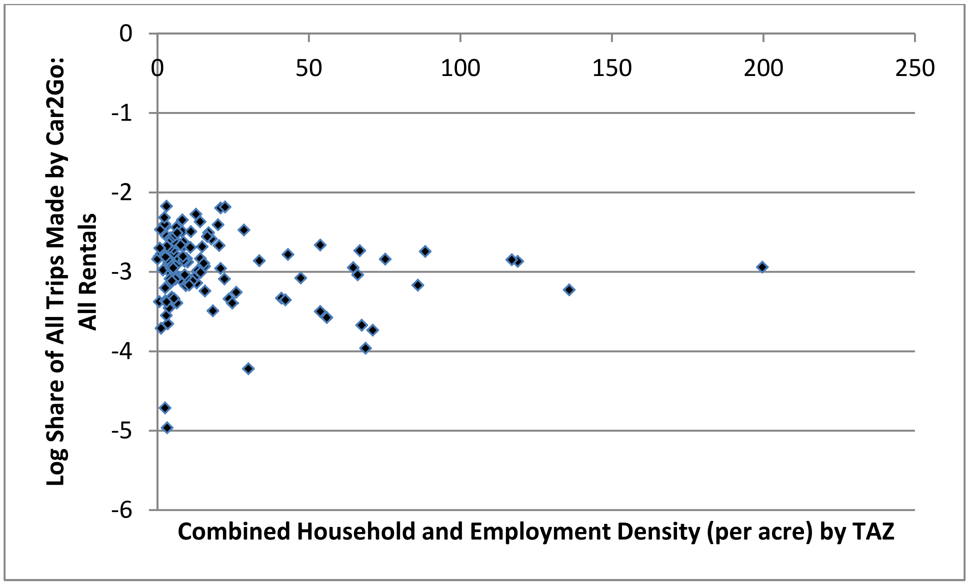

Figure 16: Log Car2Go Mode Share (All Rentals) vs. Density

The final model specifications are shown in Table 14.

Table 14: 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.

Given the previous examination of the scatter plots, the results of the model are unsurprising. Densities, average household size, and median household income all have a negative effect on the expected carsharing mode share expected. As discussed above, household size is an expected result. The negative impact of densities is likely connected to the increased number of overall trips in dense areas; the relative increase in trips made by carshare in such areas is not as great as the rate of increase of the overall trips, although the absolute value of number of carshare trips is higher than in areas of low density.

5.2.2 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. Because the data provided by CAMPO 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-grapefruit." As in the previous methodology, this model will consider only trips made between June and December of 2010, the period in which Car2Go was open to the public.

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 15, all of which are consistent with an individual driving directly from Point A to a different Point B.

Table 15: 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 in the previous methodology, the first step is looking at scatter plots of relevant variables as compared to the dependent variable (the mode share). Figure 17 shows the relationship between mode share and average household size, which is again slightly negative.

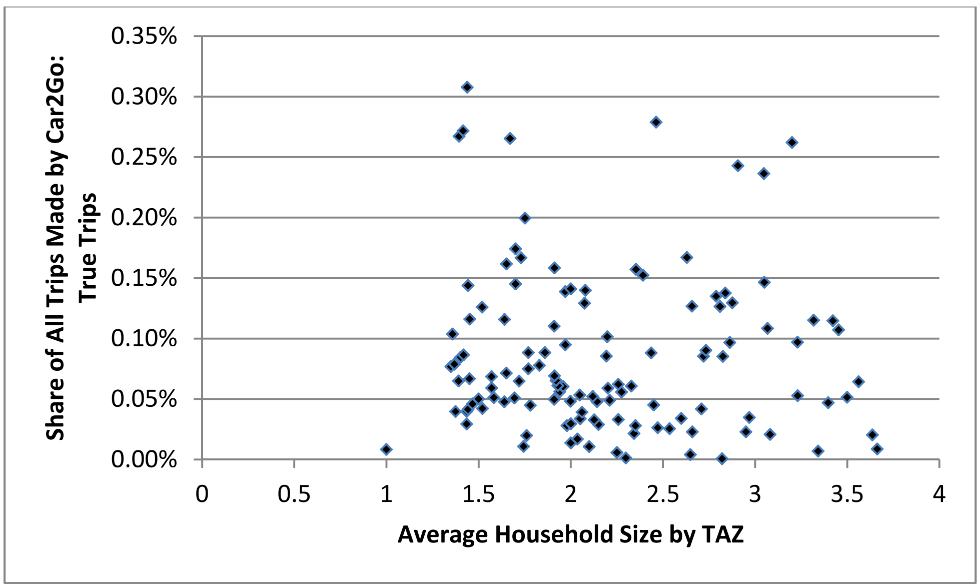

Figure 17: Car2Go Mode Share (True Trips) vs. Household Size

Figure 18 compares Car2Go's mode share to average household income, and, as before, a negative relationship exists between mode share and income, although hetereoskedasticity is clearly present.

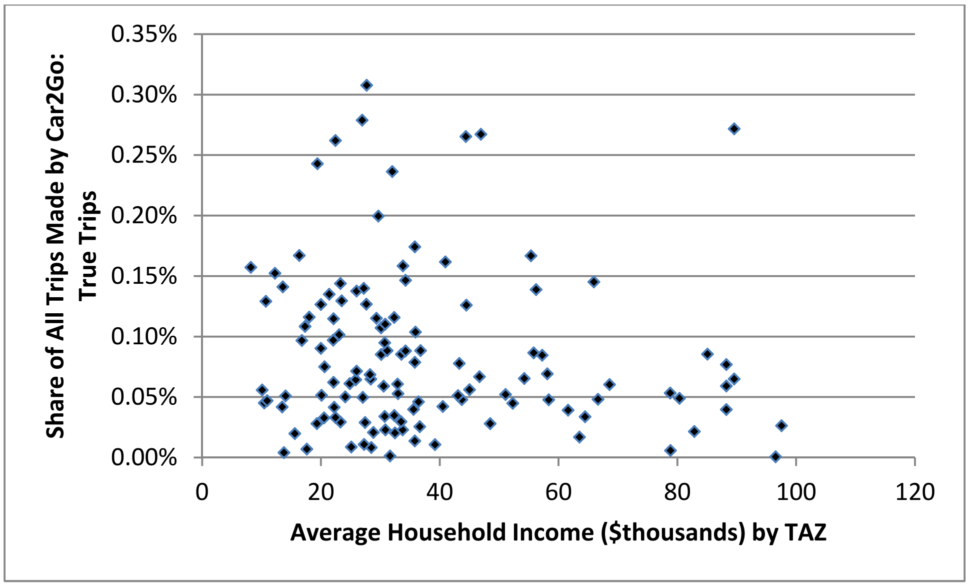

Figure 18: Car2Go Mode Share (True Trips) vs. Income

In Figure 19, the negative relationship between density and mode share that existed in the previous methodology is again present. Heteroskedasticity is particularly obvious in this figure.

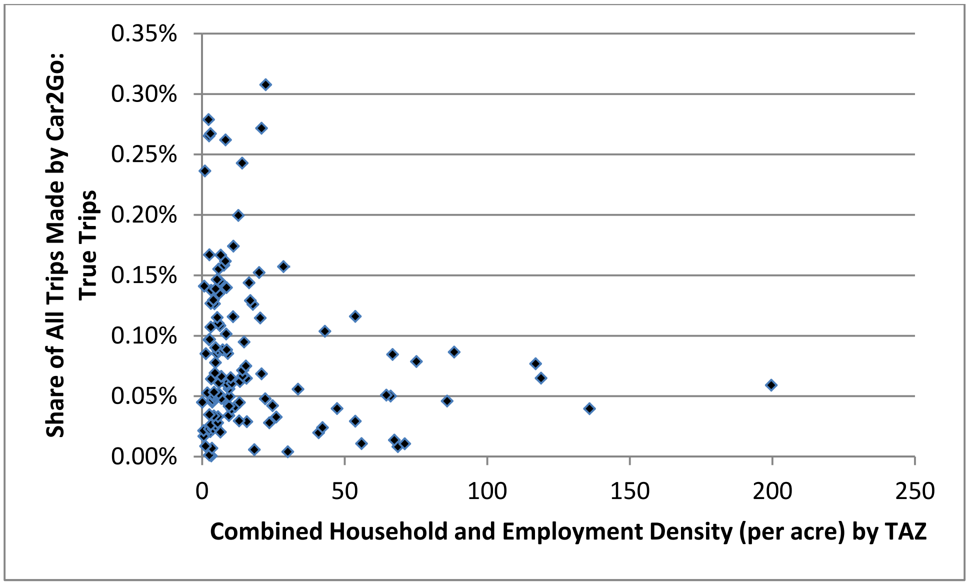

Figure 19: Car2Go Mode Share (True Trips) vs. Density

As before, the clustering effect among the low densities and low mode shares makes the details of the scatter plot difficult to see. Figure 20 shows the same plot, with the Y-axis truncated to a maximum value of 100 homes/jobs per acre.

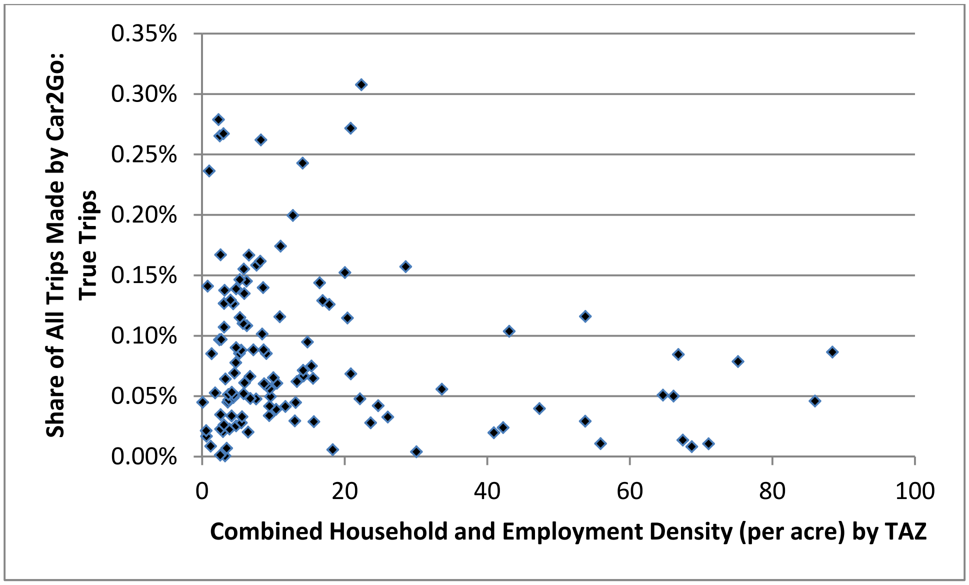

Figure 20: Car2Go Mode Share (True Trips) vs. Density - Zoom

As with the analysis of all rentals, the heteroskedasticity in the variables is quite apparent from the above scatter plots. Again, a transformation of log(y) was used, and the reduced heteroskedasticity can be seen in Figure 21, Figure 22, and Figure 23 below.

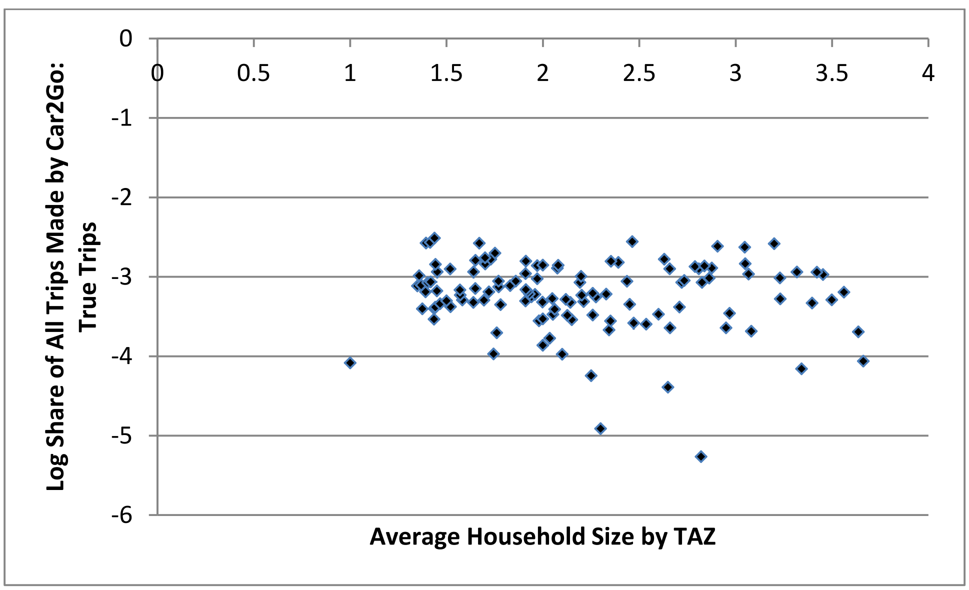

Figure 21: Log Car2Go Mode Share (True Trips) vs. Household Size

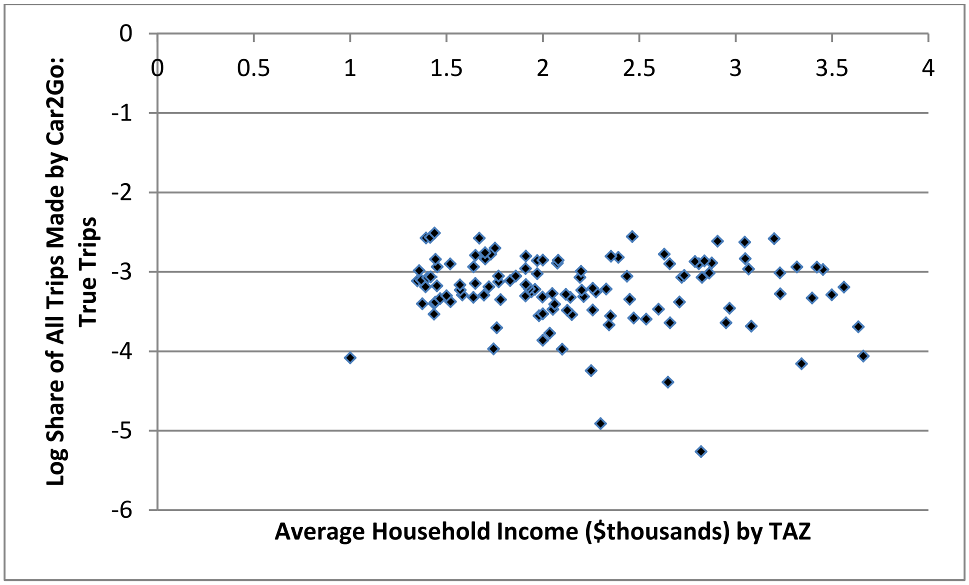

Figure 22: Log Car2Go Mode Share (True Trips) vs. Income

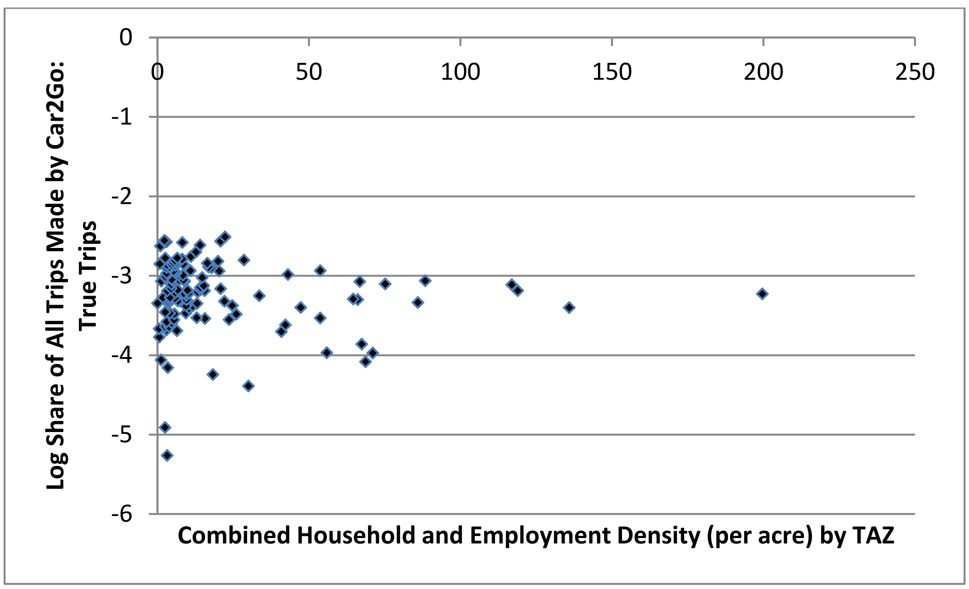

Figure 23: Log Car2Go Mode Share (True Trips) vs. Density

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, based on the similarities of the relationships shown by these scatter plots to the scatter plots for all rentals, it is reasonable to assume that the models for "all rental" mode share and for true trip" mode share may also be similar. This is in fact the case; the model specifications for true trip mode share are shown in Table 16.

Table 16: 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 16. 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.

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.

5.2.3 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).

The following methodologies use a variety of dependent variables. The first sets the dependent to the total number of 2010 rentals per person in a census block. Using OLS regression, one variable overtakes all others in statistical significance: the percent of the population that is a member. See Table 17.

Table 17: Rentals per Person Model Specification

Variable	B	Std.Err.	Sig.
Constant	-0.561	0.335	0.093
Percent of population that is a member	0.513	0.030	0.000
			N=2,890 Adjusted R^2: 0.195

No other combination of explanatory variables provided any level of sufficient explanation of the person-split of carsharing. It is not surprising that member percentage provides a strong explanation, but the difficulty of assessing the proportion of the population that is a carsharing member makes this model of limited immediate direct use for MPOs and other planning agencies. Instead of using the model directly, the planning agency would need to first use one of the member prediction models from the previous chapter, then use the results of those models as inputs for the person-share of carsharing.

Another possible alternative is to consider only the members in a census 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 OLS model of Table 18 emerges:

Table 18: 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			

Some of the variables in this model are quite familiar, as they have appeared in many of the models previously developed. 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 become statistically significant for the first time 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 do 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 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 24.

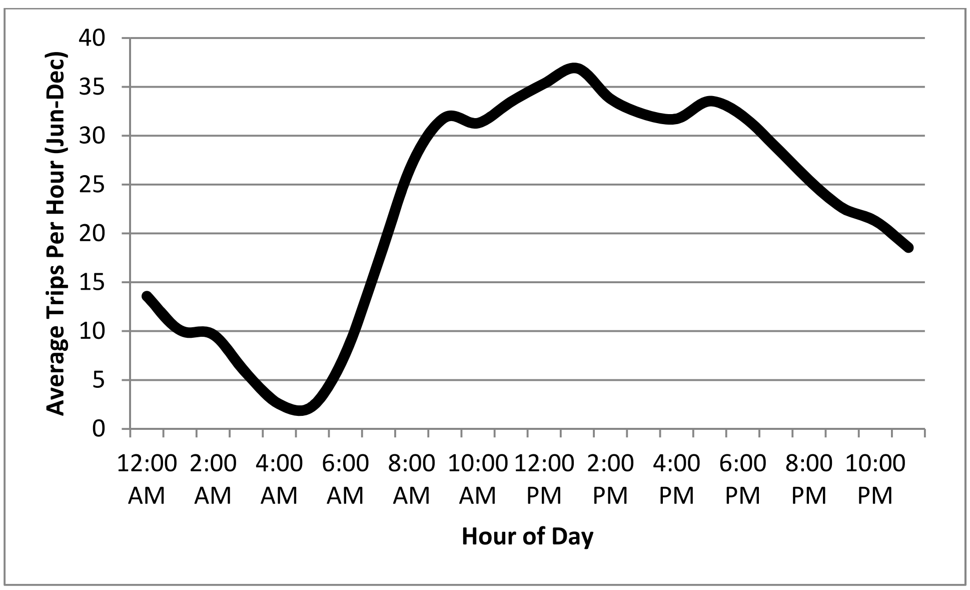

Figure 24: Average Rentals by Hour

If a significant proportion of the Car2Go trips had been home-based work trips, a graph of usage by hour of day would show significant peaks during the morning rush hour (approximately 7am-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 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 is less dependent on only the residential attributes of the area, considering 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 19.

Table 19: 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. 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.

Chapter 6: Allocation Modeling

6.1 Literature Review

Every carsharing operation must decide where exactly to operate and where to locate the vehicles. In the case of most traditional carshare organizations, this is defined as the location of the vehicle's "home" parking spaces. Instead of providing anchor parking spaces, Car2Go instead allows vehicle rentals to be ended anywhere within its operating area, making determinations of allocation area unique to them. During the study period of 2010, the operating area was approximately 32mi^2, encompassing the central portion of the Austin metropolitan area and including both the central business district and the University of Texas. Vehicles may be driven outside of the operating area, but rentals may not be ended until the vehicle is within the geofenced area.

Most existing literature on carsharing allocation issues focuses on traditional systems with fixed vehicle locations. For example, Morency et al.'s 2008 analysis considers potential anchor locations for a carsharing program in Montreal, describing some of the challenges associated with the variability in attractiveness of each vehicle location. The differences in attractiveness from station to station and from year to year complicate the vehicle allocation process, resulting in a need for advanced analytical models that can handle these complexities.

Several studies in recent years have looked at the relocation of carshare vehicles. Kek et al. (2006) used a time-stepping simulation model to aid vehicle operators in best reallocating carsharing vehicles. Using local carsharing data as a validation measure, this model was able to generate cost savings of approximately 13% without any changes in level of service for the users. Later, Kek et al. (2009) used a three-phase optimization-trend-simulation decision support tool to show reduced staff needs, unused vehicle time, and number of needed vehicle relocations. Using simulation data from a carsharing operator in Singapore, they found a recommended set of parameters for vehicle relocation operations that reduced staff costs by 50%, empty-vehicle time by up to 13%, and vehicle relocation movements by up to 41%. The authors point out that these savings could result in a significant increase in profitability.

Other researchers have also looked at similar allocation optimization issues. Fan et al. (2008) created a multistage stochastic linear integer model with recourse to account for the large number of demand-related uncertainties in any traditional carsharing operation. In combination with a Monte Carlo sampling-based stochastic optimization method, Fan et al. found that the proposed model could help to determine optimal allocations for a real-world operation. While the results were promising, the authors acknowledged the limitations of the artificial and small data set they were using and the need for further research to use actual data provided by a carsharing organization to further refine the model. Wang et al. (2010) found that microscopic traffic simulation models could be used to improve the allocation of vehicle resources for carsharing programs in Singapore. Correia and Antunes (2012) considered the location decisions for one-way carsharing models, although in their case, they focused on the location of a set number of depots to which the vehicles must be returned, a more limited situation that that faced by Car2Go's free-floating scheme. They found that one-way systems were much riskier than traditional round-trip carsharing schemes and that a limited number of depots located within the CBD of a city would provide the best opportunity for financial success.

All carsharing programs include a number of empty-vehicle movements. Traditional operators put this burden on the user as he brings the vehicle back to its home location. Free-floating operators, which allow users to avoid making unneeded return trips, must consider these trips as they work to optimize the allocation of vehicles. The extent of these movements and the cost associated with each can have a significant impact on the potential profitability of the carsharing organization, and therefore the organizations seek ways to minimize the need for these vehicle movements. Price incentives are one possibility; users are charged more for leaving a vehicle at an out-of-the-way location or in an over-supplied neighborhood. On the other hand, users also receive discounts for leaving a vehicle in locations where vehicles are scarcer. During 2010, Car2Go did not offer any incentives to move a vehicle from an area of low utilization to an area of higher demand, but this may become part of their business plan in future years.

The carsharing allocation optimization issue has certainly been considered, as have a number of similar problems involving the location of depots for various resources (buses, ambulances, warehouses, etc.). However, none of the solutions provided to date have allowed for truly free-floating vehicle allocation. Allocating traditional carshare vehicles to depots has distinct similarities to allocating free-floating carshare vehicles to various zones or locations around a city, but the traditional analyses requires that the vehicles return to their original location, or to another depot within the city. This dissertation provides a model to use (and expand in the future) for free-floating, one-way carsharing systems.

6.2 One-Way Vehicle Allocation Modeling

An allocation optimization model for a free-floating carsharing service was developed for this dissertation. The program's C++ code can be found in Appendix A. Given demand levels in a variety of zones and the time to travel among the zones (and, at $0.35 per minute, the revenue), the program determines the optimal allocation to maximize total revenue. After an initial allocation, vehicles move from zone to zone according to relative levels of demand, only stopping when there is no additional unmet demand in the system or when the vehicles end in a zone with no additional demand to carry it into another zone. As written, the program is designed for three zones, but could be expanded as needed to encompass all zones in the study area. Processing time would, of course, increase correspondingly.

The modeling methodology is unique in that it calculates optimal allocation for multiple demand periods, taking into account the costs of reallocating vehicles between periods to determine maximum possible revenue. During the first demand period, vehicles move from zone to zone until the unmet demand is either satisfied or unable to be satisfied due to the final locations of the vehicles. At this point, the second demand period begins, the vehicles are relocated, and the allocation optimization process begins again. As vehicles are moved to their new positions to start the second demand period, the model keeps track of the costs of moving these vehicles (based on the previously-defined travel cost matrix). After the second time period comes to an end, the revenues from the two time periods are summed and the reallocation costs for each vehicle distribution option are subtracted from the total.

Given the total number of vehicles to be distributed through the system (a number provided by the user at the beginning of the program's run) this methodology considers all possible allocations of those vehicles for each of the two time periods. Because of this, the number of possible allocation scenarios grows very quickly. For example, if only three vehicles are used in the three zones, ten possible allocation scenarios exist for the first time period: [3,0,0], [2,1,0], [2,0,1], [1,2,0], [1,1,1], [1,0,2], [0,3,0], [0,2,1], [0.1.2], and [0,0,3]. After each of these ten options is analyzed, the methodology considers the same ten alternatives for the second time period of each option, resulting in a total of 100 complete scenarios.

To demonstrate the use of the model, consider the following demand matrix for the first time period:

Zones	**1**	**2**	**3**
1	0	2	3
2	4	0	5
3	6	2	0

In the second time period, the demand matrix changes as follows:

Zones	**1**	**2**	**3**
1	0	4	4
2	2	0	2
3	3	5	0

Also consider the following travel time (and revenue) matrix, which is constant across both demand periods:

Zones	**1**	**2**	**3**
1	0	3	2
2	2	0	2
3	4	2	0

For the purposes of this example, there is no intra-zonal demand, and the intra-zone travel time is trivial. The user provides the total number of vehicles to be allocated in the system. Vehicles are moved in fractional form, as the fractions become trivial as the number of zones and vehicles approach practical sizes.

If the user chooses to spread three vehicles throughout the example system, the maximum total revenue is 89.80 (revenue of 48.91 in period one, revenue of 40.88 in period two, and reallocation costs of 0.09) with optimal allocations of [0,1,2] in the first time period and [3,0,0] in the second time period. If the user chooses instead to allocate five vehicles, the maximum total revenue of 102.46 (revenue of 57.98 in period one, revenue of 44.50 in period two, and reallocation costs of 0.01) occurs with optimal allocations of [0,5,0] in the first time period and [5,0,0] in the second time period. Complete results of each program run can be found in Appendix B.

Although it becomes less efficient as the number of zones grows, this methodology will work for larger systems as well. For example, in a twenty-zone system, the same methodology can be used to distribute 100 vehicles (an example problem more analogous to a realistic carsharing fleet in a small city). Using random numbers to represent both the demand loads and travel times/costs (and allowing for both intrazonal demand and travel time) results in two example origin-destination matrices and a travel time matrix, all three of which can be found in Appendix C. Using these random demands and travel costs, the maximum total revenue is 576.44 (revenue of 61.73 in period one, revenue of 579.52 in period two, and reallocation costs of 64.80). The optimal distribution of the 100 vehicles can be seen in Table 20 below. As in the example with five vehicles in a smaller system, the optimal allocation is not equally distributed among the zones due to uneven demands and the costs of reallocating the vehicles between demand periods.

Table 20: Twenty Zone Optimal Allocation

Zone	Period 1	Period 2
1	0	0
2	0	7
3	0	0
4	2	0
5	1	1
6	60	3
7	0	0
8	1	70
9	0	0
10	6	0
11	15	0
12	1	0
13	0	5
14	0	9
15	3	5
16	3	0
17	5	0
18	0	0
19	0	0
20	3	0

Carsharing organizations may use this methodology to determine where cars should best be placed in order to maximize revenue. In combination with an analysis of the fixed and variable costs of operating vehicles, this model can determine the total profit a carsharing organization can expect to achieve.

6.3 Future Additions to Allocation Model

This allocation model is a first step in an eventual robust allocation modeling methodology. There are a number of opportunities for expansion of this model to make it more applicable to existing carsharing organizations.

First of all, the program can be expanded to account for systems larger than three to twenty zones. Depending on the metropolitan area under consideration, a carsharing organization may wish to use traffic analysis zones as defined by the local metropolitan planning organization. Vehicles could then be placed strategically throughout the TAZs (on main streets or near major attractors). Alternatively, a carsharing organization could consider its usage data to develop its own system of zones. These zones may be smaller, eliminating the question of where to locate vehicles within the zones, or may be more closely tied to demonstrated carsharing demand, which is unlikely to be the same as general travel demand.

On a similar note, one-way carsharing organizations (Car2Go and others under development) could use their existing usage data as demand data, thus making the results specific to their own operations. The demand data could be updated over time as demand changes and the system settles into consistent usage patterns. Using existing carsharing demand data instead of existing trip-making estimates would improve the precision of the model. The random numbers used in the examples above are intended to highlight the methodology, not the likely results for an actual carsharing program.

As currently written, the program contains two demand periods, and the vehicles move until the initial demand in each period is satisfied or until there is no demand remaining to move the vehicles any further. Including additional demand periods to account for demand over the course of a day, week, or other practical period of time would add realism to the modeling of the vehicle movements. The time periods used in this analysis could be days, hours, or portions of a day (for example, morning rush hour, mid-day, afternoon rush hour, evening, and overnight). The differences in rental patterns during different times of day were discussed in Chapter 5 in the discussion of potential trip purposes, and these differences can drive the demand period designations. Eventually, the demand could become dynamic instead of the current static system. Unmet demand is not likely to remain if it is not met in the first iteration of car movements, as is the case in the current methodology; future analysis could assume that a certain portion of unmet demand disappears and new demand levels emerge. The travel time matrix can also change along with the demand, better representing changing travel conditions throughout a day or other time period.

In existing carshare operations, the vehicles are not limited to moving only when users drive them from place to place; employees of the carsharing program also relocate the vehicles as needed, whether to areas of higher demand or away from areas of low demand. Employees may temporarily take a vehicle out of service for maintenance or cleaning, replacing it in either the same or a different location. Including more information about the forced reallocation of the vehicles would also improve the practicality of the program. Carsharing organizations could allow for a limited number of vehicle moves per day (or per demand period), or they could adjust settings such that vehicles remaining in one place for a set period of time are moved to areas of higher demand to keep them in circulation. The current method of forcing a complete reallocation of vehicles with each new demand period is not practically feasible.

From an optimization standpoint, improvements in methodologies are also possible. The current program uses a “brute force” method to determine the optimal allocation solution, enumerating all possible options for allocation of the vehicles and calculating the revenue generated by each. More sophisticated optimization techniques are possible and will be needed as the size of the study area increases.

Chapter 7: Conclusion

7.1 Discussion

Carsharing, the rental of a vehicle by the minute or the hour, is a concept that is decades old, but it has become much more common in recent years. At the end of 2009, the carsharing organization Car2Go, run by Daimler Auto Group, began operating in Austin. Using data provided by Car2Go about its members and its rentals, this dissertation has created new methodologies to understand the membership and usage of this new style of free-floating carsharing system.

Exploratory analysis of the data shows that Car2Go members are concentrated in the central part of the city, an entirely expected finding. More interestingly, in the zip code corresponding to downtown Austin, one in six residents is currently a Car2Go member. High proportions of members can also be found in the neighborhoods around the university and just outside of downtown. Members tend to join at much higher rates when Car2Go puts on a promotional activity, with significant spikes in membership occurring when the program opened to the public and when the free membership period was about to expire. As the membership has grown more diverse than the initial City of Austin employees who made up the pilot test group, the vehicles have been used during larger parts of both the day and the week; weekend and after-work rentals were nearly non-existent in the program's initial months, but now carsharing is just as likely to occur on Saturday as Tuesday and it also occurs at all hours of the day and night. As members have grown more comfortable with the service, they have also become more efficient in their use of the service, taking advantage of the one-way option.

A study of metropolitan areas examines objective characteristics that make a city likely to have a successful carsharing program. Unsurprisingly, population is a key factor, as larger cities are more likely to have carsharing services than are small cities. Smaller average household sizes and larger fractions of the population commuting via transit also make a city more amenable to carsharing. Most interestingly, increasing numbers of government workers in a metropolitan area also increase the likelihood of carsharing succeeding; this may be connected to the many governmental agencies contracting with carsharing services to reduce their own fleet sizes and the associated costs of owning the vehicles. Ethnicity, median age, and household income, all of which have appeared as significant variables in previous carsharing literature, did not prove to be statistically significant in this analysis.

Membership prediction is of great importance to carsharing organizations as they plan their operational characteristics. Several alternatives to this prediction are possible, including two-step models and a one-step model. In the two-step version, binary logit modeling determines which census blocks are likely to contain any members, and either linear regression or logit modeling estimates the proportion of those blocks that are members. The preferred alternative, however is a one-step Heckman sample selection model, which correlates the errors in the two dependent variables (binary membership and continuous membership proportions). The Heckman sample selection model shows that the geofence location is a vital factor in determining membership, as are household size, fraction of commuters using transit, age, race, and proportion of 20-39 year olds living in an area.

Mode share modeling is another innovative methodology introduced in this dissertation. 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 surprisingly robust measure of the total carshare trips in any zone.

Finally, allocation modeling for a free-floating carsharing system is another innovative methodology. Previous studies of optimal allocations for carshare vehicles assumed the vehicles must be 1) located at a limited number of depots and 2) brought back to the depot at the end of the usage period. Because neither of these considerations is true in the case of free-floating carsharing systems, a new methodology was needed. This dissertation provides a solution technique, using C++ programming, to optimize the location of vehicles during multiple demand periods in order to optimize the total revenue generated by the demand-driven movement of the vehicles. The program also takes into account the costs of reallocating the vehicles between demand periods.

7.2 Reasons Not to Use Carsharing

7.2.1 All Carsharing

While carsharing is increasing in popularity throughout North America and worldwide, there are still a number of reasons that an individual or household may decide that carsharing is not a viable option for their lives. These reasons are not necessarily found in the empirical data collected by carsharing organizations over the years, but are instead based on anecdotes and postulations on human behavior and decision-making.

Carsharing works only if vehicles are available and convenient to potential members. Carsharing organizations must carefully decide how many vehicles to place in any given area in order to ensure that vehicles are reasonably convenient to a large number of members. If vehicles are rarely available within the distance that an individual is willing to travel to reach the vehicle, he or she is unlikely to obtain or retain a membership. Each member will determine for himself the distance he is willing to travel to reach a carsharing vehicle, and this distance is likely to vary based on weather, cargo, time of day, and a variety of other factors. Those living on the periphery of the carsharing operating area may not consider the service to be convenient for them because of limited vehicle availability.

Carsharing is generally not appealing to parents with small children because of the “carseat issue.” Children are required to be secured in a carseat when traveling in any vehicle, and parents must supply their own carseat in a carsharing vehicle. Most families who do not own a vehicle will not own a carseat to begin with. Not only is it a burden to transport the usually bulky carseat in addition to the small child and any other purses, bags, or additional luggage, but the parent must then ensure that the carseat is properly fastened in the carsharing vehicle. News reports routinely alert parents that most carseats are improperly installed (e.g., “A Look Inside”, 2011); therefore most parents prefer to install the carseat once in their own vehicle, possibly have its installation checked by a professional, and then be confident that the carseat is installed correctly for all future trips. The challenges of traveling with small children and carseats keep most parents from considering carsharing to be a viable transportation alternative.

Carsharing organizations rely heavily on technology to function – reservations are made online, vehicles are unlocked by waving a membership card over a sensor, and GPS keeps track of the vehicle at all times, for example. Occasionally, for a variety of reasons, the technology fails to function as expected and the member has trouble starting, ending, or being correctly charged for a rental. This type of issue is most common when the carsharing operation is new, at the very time that it is trying to make the best possible impression on its members. Members and potential members can be quickly turned off of the service when it does not prove to be easy to use. Many potential and former carshare members have ended (or failed to begin) their memberships because of the existence or perception of such challenges in the rental logistics.

Many individuals have a flawed perception of the cost of their transportation choices. Because many of the expenses of owning and operating a private vehicle are fixed (such as purchase cost, insurance, and maintenance) largely regardless of the amount of use the vehicle sees, the perceived cost of driving is often only that of gas and tolls. Because the hourly cost of carsharing encompasses all of these vehicular costs, it is often seen as being more expensive than using a private vehicle, particularly when the individual already owns the vehicle.

Liability concerns also prevent some from choosing carsharing. If a vehicle is reported as damaged by a renter, the fault for the damage falls on the previous renter, even though the damage may have occurred after the previous renter completed his or her rental. Carsharing organizations have a variety of policies in place to address this issue (Lieber, 2011), but the perceived liability issues are a deterrent for some potential members.

Many programs have limits on the free mileage provided for each rental. Zipcar, for example, provides 180 free miles per day. For most urban trips, this is not a problem, but for longer trips that last most of a day, the expense associated with the extra miles can make the vehicle rental prohibitively expensive. In this case, individuals would often be better-served to use their own vehicle or rent a vehicle from a traditional rental operation.

Nearly all carsharing organizations will require a relatively clean driving record as a prerequisite for membership. Speeding tickets and minor accidents generally will not preclude an individual from membership, but major accidents for which the individual is at fault often will. Those with less-than-clear driving backgrounds are likely to be unable to obtain membership at all.

Carsharing requires some level of planning ahead, whether that means reserving a vehicle up to a week in advance or walking from the origin to the vehicle location. This extra time requirement is often a barrier to many individuals using carsharing.

7.2.2 Car2Go

The largest flaw with the Car2Go business plan is the lack of variety in vehicles available to members. All of the vehicles in each of their fleets are the same: a Smart ForTwo, although the engine type varies by city (diesel engines in Europe, gasoline in Austin and Vancouver, electric in San Diego). As has been well-documented, many of those who are carsharing members do not own a personal vehicle and use transit, walking, or bicycling for a majority of their travel. However, when these individuals do need a vehicle, they tend to need to transport something or someone that requires space – new furniture, a group of travelers, or some other large object(s). The Smart ForTwo does not have the type of cargo capacity that many of these individuals need in a vehicle. The small vehicles also preclude groups of more than two from choosing carsharing, unless the group contains multiple Car2Go members and they drive separately.

Currently, Car2Go does not provide bike racks for any of their vehicles. As the vehicles have limited interior cargo space, a member is therefore unable to travel with a bicycle (unless the bicycle is of the compact folding variety). Anecdotally, many members have expressed a desire to be able to bike either from their origin to the vehicle to begin a rental, or from the end of their rental to the final destination. If a member's origin or destination point is outside of the geofence, Car2Go would only be able to allow the member to be close to that point; walking, bicycling, or transit would be needed to go the first or last mile of the trip. Including bicycle racks on all vehicles would effectively extend the geofence slightly for those willing to bike to or from a vehicle.

7.3 Contributions

This dissertation contributes to the state of the art of carsharing knowledge in several ways. First of all, it provides methodologies to predict membership given the demographic characteristics of a metropolitan area and the operating area of the carsharing program. Previous academic analysis of member characteristics has looked at those who are already members of a carsharing program and attempted to determine what makes this subset of individuals different from the population at large. This analysis considers the question of membership from the opposite direction – given the population at large, who is likely to become a member? Carsharing organizations have undoubtedly done some research of this type on their own, but the analyses are proprietary and not in the public domain. Therefore, this dissertation provides needed information for both carsharing providers, who will have a better sense of their potential membership profiles and therefore optimal operating areas, and for planning agencies, which will be better able to attract carsharing services with a detailed description of how and where the service can be successful.

Second, the mode share analysis undertaken here is the first known mode share analysis exclusively dedicated to carsharing. 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.

Third, this dissertation outlines a solution method for optimizing the allocation of vehicles in a free-floating carsharing system. Daimler AutoGroup's Car2Go is the largest and best-known of these systems to date, but other carsharing systems, including BMW's DriveNow operation, have taken note of Car2Go's success and will be replicating its structure. Existing allocation optimization methodologies, which are based around the concept of returning the vehicle to a particular depot when the rental is completed, are not sufficient for these free-floating systems. The methodology provided here, with added complexity as needed, can provide profit-maximization techniques to these carsharing organizations. Planning organizations would also be well-served to consider this methodology, as they may be able to influence carsharing systems' vehicle placements to best handle travel demand throughout the metropolitan area.

7.4 Future Work

Compared to driving, transit, and non-motorized modes, carsharing is a new transportation alternative and faces a great many unknowns. While this dissertation addresses several of the questions that must be answered for carsharing to become a truly viable alternative, many questions remain.

Additional work is needed to better understand the trip purposes of all carshare users, especially those using free-floating systems. When there is no requirement to bring the vehicle back to the starting point of the rental, users have more flexibility in their rentals and the trip purposes may be significantly different than in traditional carsharing systems. The modeling of section 5.2.3 confirms the hypothesis that there is not a strong relationship between demographic characteristics of residents and trips made; as a result, it is likely that many of the trips being made are not home-based and thus home demographics are unrelated to tripmaking. Because of this, performing carsharing mode share analyses that are analogous to traditional mode share analyses may not be an effective way to predict carshare trips. Surveys of users are likely to assist in efforts to better identify trip purposes.

The data used throughout this dissertation is based on the first year of Car2Go's Austin operations. While it is a large dataset with a great deal of useful information about the first year, additional study is needed on later operations of the system, once usage settles into more stable patterns. As reported in section 2.4.2, new members were joining the program throughout 2011. Many of these users may have been curiosity-driven, renting a vehicle and driving it without a specific trip purpose so they could test out the system or the Smart ForTwo. This type of trip would certainly confound any type of mode split analysis, and those who joined the program only to drive a vehicle once may not be representative of the typical member profile. Additional analysis over a longer time period would undoubtedly reveal new insights into the free-floating carsharing system and show long-term trends.

The allocation model is unique in its application to a free-floating carsharing system, but in order to be truly useful to carsharing organizations, it needs to be expanded. The example of a three-zone system would need to be enlarged; using the TAZ system in Austin as a starting point would require 126 zones, and these may be broken down further as needed. Including additional demand periods, eventually shifting the demand to a dynamic input instead of its current static form, would also greatly improve the utility of the methodology, as would the addition of reallocation criteria to meet practical demands. Finally, the program's optimization techniques will need to be made more efficient as the area of analysis and the number of vehicles grow larger.

7.5 Summary

As carsharing continues to expand throughout the United States, organizations considering starting a program in their own community will need analytical methods for determining the viability of a potential operation. Free-floating carsharing operations, including Car2Go, face challenges unlike traditional carsharing organizations due to the unique nature of their one-way rentals that can end in any legal parking space, not only at a set number of depots. In addition, metropolitan planning organization and other transportation planning agencies will be faced with a need to estimate carsharing's mode split in upcoming years as carsharing becomes a more prominent transportation alternative. This dissertation provides methodologies to guide both metropolitan areas and carsharing organizations through the startup process, beginning with the decision of which cities are best suited for carsharing, predicting membership, estimating the total trips made by the carsharing organization, and finally optimizing the vehicle allocation process.

Appendix A: Allocation Model C++ Program Code

```
#include <iostream>
using namespace std;

// declaring function prototypes
float addition (float a, float b);

//main function
int main ()
{
//initalize variables
int totalcars;
float revenue1;
float revenue2;
float maxrevenue=0;
float startdemand[3][3]={{0,2,3},{4,0,5},{6,2,0}};
float startdemand2[3][3]={{0,4,4},{2,0,2},{3,5,0}};
float demand[3][3];
float zonedemand[3]={0,0,0};
float traveltozone[3]={0,0,0};
float cost[3][3]={{0,3,2},{2,0,2},{4,2,0}};
float travel[3][3];
float unmet[3][3];
float startcars1[3];
float startcars2[3];
float maxcars[3];
float cars[3];
float totalunmet=0;
float totalunmetOLD;
float reallocatecost;

//sum rows of demand matrix
for (int a=0;a<3;a++)
   for (int b=0;b<3;b++)
      zonedemand[a]=zonedemand[a]+demand[a][b];

//input the total number of cars to be distributed among zones
cout << "What is the total number of cars? ";
cin >> totalcars;

//run for all possible combinations of vehicles in zones - STAGE ONE
for (int i=totalcars;i>=0;i--)
   for (int j=0;j<=totalcars-i;j++)
      {
      revenue1=0;
      cars[0]=i;
      cars[1]=j;
      cars[2]=totalcars-i-j;
      startcars1[0]=cars[0];
      startcars1[1]=cars[1];
      startcars1[2]=cars[2];
      zonedemand[0]=0;
      zonedemand[1]=0;
      zonedemand[2]=0;
      reallocatecost=0;

      for (int a=0;a<3;a++)
         for (int b=0;b<3;b++)
```

```
      demand[a][b]=startdemand[a][b];
for (int a=0;a<3;a++)
   for (int b=0;b<3;b++)
      zonedemand[a]=zonedemand[a]+demand[a][b];

//create first TRAVEL table
for (int a=0;a<3;a++)
   for (int b=0;b<3;b++)
      travel[a][b]=demand[a][b]/zonedemand[a]*cars[a];

//create first UNMET demand table and calculate total unmet demand
for (int a=0;a<3;a++)
   for (int b=0;b<3;b++) {
      if ((demand[a][b]-travel[a][b])>0)
         unmet[a][b]=demand[a][b]-travel[a][b];
      else unmet[a][b]=0;
   }
for (int a=0;a<3;a++)
   for (int b=0;b<3;b++)
      totalunmet=totalunmet+unmet[a][b];

//calculate REVENUE for first period
for (int a=0;a<3;a++)
   for (int b=0;b<3;b++)
      revenue1=revenue1+travel[a][b]*cost[a][b];

do {
   //calculate total number of cars into each zone in last round
   for (int b=0;b<3;b++)
      traveltozone[b]=0;
   for (int b=0;b<3;b++)
      for (int a=0;a<3;a++)
         traveltozone[b]=traveltozone[b]+travel[a][b];

   //calculate new number of CARS in each zone
   for (int a=0;a<3;a++) {
      if (cars[a]>zonedemand[a])
         cars[a]=cars[a]-zonedemand[a]+traveltozone[a];
      else cars[a]=traveltozone[a];
   }

   //create new DEMAND matrix from old unmet demand matrix and sum for
   each zone
   for (int a=0;a<3;a++)
      for (int b=0;b<3;b++)
         demand[a][b]=unmet[a][b];
   for (int a=0;a<3;a++)
      zonedemand[a]=0;
   for (int a=0;a<3;a++)
      for (int b=0;b<3;b++)
         zonedemand[a]=zonedemand[a]+demand[a][b];

   //create new TRAVEL matrix
   for (int a=0;a<3;a++)
      for (int b=0;b<3;b++)
         travel[a][b]=0;
      for (int a=0;a<3;a++)
         for (int b=0;b<3;b++)
            if (zonedemand[a]>0.005) {
               if (zonedemand[a]<cars[a])
```

```
                    travel[a][b]=demand[a][b];
                else travel[a][b]=demand[a][b]/zonedemand[a]*cars[a];
            }

    //create new unmet demand matrix and sum all unmet demand
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++)
            unmet[a][b]=0;
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++) {
            if ((demand[a][b]-travel[a][b])>0)
                unmet[a][b]=demand[a][b]-travel[a][b];
            else unmet[a][b]=0;
        }
    totalunmetOLD=totalunmet;
    totalunmet=0;
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++)
            totalunmet=totalunmet+unmet[a][b];

    //update revenue
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++)
            revenue1=revenue1+travel[a][b]*cost[a][b];
} while (totalunmet<0.99*totalunmetOLD);

//run for all possible combinations of vehicles in zones - STAGE TWO
for (int i=totalcars;i>=0;i--)
    for (int j=0;j<=totalcars-i;j++) {
        revenue2=0;
        startcars2[0]=cars[0];
        startcars2[1]=cars[1];
        startcars2[2]=cars[2];
        cars[0]=i;
        cars[1]=j;
        cars[2]=totalcars-i-j;

        //calculate reallocation costs
        if (startcars2[0]>cars[0]){
            if (startcars2[1]<cars[1])
                reallocatecost=reallocatecost+(startcars2[0]-
                cars[0])*cost[0][1];
            else reallocatecost=reallocatecost+(startcars2[0]-
            cars[0])*cost[0][2];
        }
        else {
            if (startcars2[1]<cars[1])
                reallocatecost=(cars[0]-startcars2[0])*cost[2][0];
            else reallocatecost=(cars[0]-startcars2[0])*cost[1][0];
            }
        if (startcars2[1]>cars[1])
            reallocatecost=reallocatecost+(startcars2[1]-
            cars[1])*cost[1][2];
        else reallocatecost=reallocatecost+(cars[1]-
        startcars2[1])*cost[2][1];

        zonedemand[0]=0;
        zonedemand[1]=0;
        zonedemand[2]=0;
        reallocatecost=0;
```

```
for (int a=0;a<3;a++)
    for (int b=0;b<3;b++)
        demand[a][b]=startdemand2[a][b];
for (int a=0;a<3;a++)
    for (int b=0;b<3;b++)
        zonedemand[a]=zonedemand[a]+demand[a][b];

//create first TRAVEL table
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++)
            travel[a][b]=demand[a][b]/zonedemand[a]*cars[a];

//create first UNMET demand table and calculate total unmet demand
for (int a=0;a<3;a++)
    for (int b=0;b<3;b++) {
        if ((demand[a][b]-travel[a][b])>0)
            unmet[a][b]=demand[a][b]-travel[a][b];
        else unmet[a][b]=0;
    }
for (int a=0;a<3;a++)
    for (int b=0;b<3;b++)
        totalunmet=totalunmet+unmet[a][b];

//calculate REVENUE for first period
for (int a=0;a<3;a++)
    for (int b=0;b<3;b++)
        revenue2=revenue2+travel[a][b]*cost[a][b];

do {
    //calculate total number of cars into each zone in last round
    for (int b=0;b<3;b++)
        traveltozone[b]=0;
    for (int b=0;b<3;b++)
        for (int a=0;a<3;a++)
            traveltozone[b]=traveltozone[b]+travel[a][b];

    //calculate new number of CARS in each zone
    for (int a=0;a<3;a++) {
        if (cars[a]>zonedemand[a])
            cars[a]=cars[a]-zonedemand[a]+traveltozone[a];
        else cars[a]=traveltozone[a];
    }

    //create new DEMAND matrix from unmet matrix and sum for each
    zone
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++)
            demand[a][b]=unmet[a][b];
    for (int a=0;a<3;a++)
        zonedemand[a]=0;
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++)
            zonedemand[a]=zonedemand[a]+demand[a][b];

    //create new TRAVEL matrix
    for (int a=0;a<3;a++)
        for (int b=0;b<3;b++)
            travel[a][b]=0;
    for (int a=0;a<3;a++)
```

```
                    for (int b=0;b<3;b++)
                        if (zonedemand[a]>0.005) {
                            if (zonedemand[a]<cars[a])
                                travel[a][b]=demand[a][b];
                            else travel[a][b]=demand[a][b]/zonedemand[a]*cars[a];
                        }

                //create new unmet demand matrix and sum all unmet demand
                for (int a=0;a<3;a++)
                    for (int b=0;b<3;b++)
                        unmet[a][b]=0;
                for (int a=0;a<3;a++)
                    for (int b=0;b<3;b++) {
                        if ((demand[a][b]-travel[a][b])>0)
                            unmet[a][b]=demand[a][b]-travel[a][b];
                        else unmet[a][b]=0;
                    }
                totalunmetOLD=totalunmet;
                totalunmet=0;
                for (int a=0;a<3;a++)
                    for (int b=0;b<3;b++)
                        totalunmet=totalunmet+unmet[a][b];

                //update revenue
                for (int a=0;a<3;a++)
                    for (int b=0;b<3;b++)
                        revenue2=revenue2+travel[a][b]*cost[a][b];
                } while (totalunmet<0.99*totalunmetOLD);

            cout << startcars1[0] << " " << startcars1[1] << " " <<
            startcars1[2];
            cout << ": " << i << " " << j << " " << totalcars-i-j << ": ";
            cout << revenue1+revenue2-reallocatecost << endl;
            cout << revenue1 << " " << revenue2 << " ";
            cout << reallocatecost << endl;
            if ((revenue1+revenue2-reallocatecost)>maxrevenue) {
                maxrevenue=(revenue1+revenue2-reallocatecost);
                for (int a=0;a<3;a++)
                    maxcars[a]=startcars1[a];
            }
        }
}

cout << endl << endl << "MAX REVENUE IS " << maxrevenue << "," << endl;
cout << "with an initial allocation of " << maxcars[0] << " cars in zone 1, ";
cout << maxcars[1] << " cars in zone 2, and " << maxcars[2] << " cars in zone
3.";

char ch;
ch=getchar();
while ((ch=getchar())!='\n'&&ch!=EOF);
return 0;
}
```

Appendix B: Three-Zone Allocation Model Example Results

Three vehicles:

Allocation: Period 1	Allocation: Period 2	Total Revenue	Revenue: Period 1	Revenue: Period 2	Realloc. Cost
3,0,0	3,0,0	75.75	35.01	40.88	0.14
3,0,0	2,0,1	65.72	35.01	40.66	9.94
3,0,0	2,1,0	63.17	35.01	36.10	7.95
3,0,0	1,0,2	67.51	35.01	40.43	7.93
3,0,0	1,1,1	64.93	35.01	35.87	5.95
3,0,0	1,2,0	62.40	35.01	31.32	3.93
3,0,0	0,0,3	65.28	35.01	40.16	9.89
3,0,0	0,1,2	56.80	35.01	35.64	13.85
3,0,0	0,2,1	50.27	35.01	31.09	15.82
3,0,0	0,3,0	45.58	35.01	26.50	15.93
2,0,1	3,0,0	80.49	39.69	40.88	0.09
2,0,1	2,0,1	70.40	39.69	40.66	9.94
2,0,1	2,1,0	67.85	39.69	36.10	7.95
2,0,1	1,0,2	72.19	39.69	40.43	7.93
2,0,1	1,1,1	69.61	39.69	35.87	5.95
2,0,1	1,2,0	67.08	39.69	31.32	3.93
2,0,1	0,0,3	69.95	39.69	40.16	9.89
2,0,1	0,1,2	61.48	39.69	35.64	13.85
2,0,1	0,2,1	54.95	39.69	31.09	15.82
2,0,1	0,3,0	50.26	39.69	26.50	15.93
2,1,0	3,0,0	80.40	39.62	40.88	0.10
2,1,0	2,0,1	70.33	39.62	40.66	9.94
2,1,0	2,1,0	67.78	39.62	36.10	7.95
2,1,0	1,0,2	72.12	39.62	40.43	7.93
2,1,0	1,1,1	69.54	39.62	35.87	5.95
2,1,0	1,2,0	67.00	39.62	31.32	3.93
2,1,0	0,0,3	69.88	39.62	40.16	9.89
2,1,0	0,1,2	61.41	39.62	35.64	13.85
2,1,0	0,2,1	54.88	39.62	31.09	15.82
2,1,0	0,3,0	50.19	39.62	26.50	15.93
1,0,2	3,0,0	85.04	44.30	40.88	0.15
1,0,2	2,0,1	75.01	44.30	40.66	9.94
1,0,2	2,1,0	72.45	44.30	36.10	7.94
1,0,2	1,0,2	76.80	44.30	40.43	7.93
1,0,2	1,1,1	74.22	44.30	35.87	5.95

1,0,2	1,2,0	71.69	44.30	31.32	3.93
1,0,2	0,0,3	74.56	44.30	40.16	9.89
1,0,2	0,1,2	66.09	44.30	35.64	13.85
1,0,2	0,2,1	59.56	44.30	31.09	15.82
1,0,2	0,3,0	54.87	44.30	26.50	15.93
1,1,1	3,0,0	85.10	44.28	40.88	0.06
1,1,1	2,0,1	75.00	44.28	40.66	9.94
1,1,1	2,1,0	72.44	44.28	36.10	7.95
1,1,1	1,0,2	76.78	44.28	40.43	7.93
1,1,1	1,1,1	74.21	44.28	35.87	5.95
1,1,1	1,2,0	71.67	44.28	31.32	3.93
1,1,1	0,0,3	74.55	44.28	40.16	9.89
1,1,1	0,1,2	66.08	44.28	35.64	13.85
1,1,1	0,2,1	59.55	44.28	31.09	15.82
1,1,1	0,3,0	54.85	44.28	26.50	15.93
1,2,0	3,0,0	85.02	44.21	40.88	0.07
1,2,0	2,0,1	74.93	44.21	40.66	9.94
1,2,0	2,1,0	72.37	44.21	36.10	7.95
1,2,0	1,0,2	76.71	44.21	40.43	7.93
1,2,0	1,1,1	74.14	44.21	35.87	5.95
1,2,0	1,2,0	71.60	44.21	31.32	3.93
1,2,0	0,0,3	74.48	44.21	40.16	9.89
1,2,0	0,0,3	66.01	44.21	35.64	13.85
1,2,0	0,1,2	59.48	44.21	31.09	15.82
1,2,0	0,2,1	54.78	44.21	26.50	15.93
0,0,3	3,0,0	58.57	48.00	26.50	15.93
0,0,3	2,0,1	78.71	48.00	40.66	9.94
0,0,3	2,1,0	76.16	48.00	36.10	7.94
0,0,3	1,0,2	80.50	48.00	40.43	7.93
0,0,3	1,1,1	77.92	48.00	35.87	5.95
0,0,3	1,2,0	75.39	48.00	31.32	3.93
0,0,3	0,0,3	78.27	48.00	40.16	9.89
0,0,3	0,1,2	69.79	48.00	35.64	13.85
0,0,3	0,2,1	63.26	48.00	31.09	15.82
0,0,3	0,3,0	58.57	48.00	26.50	15.93
0,1,2	3,0,0	89.70	48.92	40.88	0.09
0,1,2	2,0,1	79.62	48.92	40.66	9.94
0,1,2	2,1,0	77.07	48.92	36.10	7.95
0,1,2	1,0,2	81.41	48.92	40.43	7.93

0,1,2	1,1,1	78.84	48.92	35.87	5.95
0,1,2	1,2,0	76.30	48.92	31.32	3.93
0,1,2	0,0,3	79.18	48.92	40.16	9.89
0,1,2	0,1,2	70.70	48.92	35.64	13.85
0,1,2	0,2,1	64.17	48.92	31.09	15.82
0,1,2	0,3,0	59.48	48.92	26.50	15.93
0,2,1	3,0,0	89.62	48.84	40.88	0.09
0,2,1	2,0,1	79.55	48.84	40.66	9.94
0,2,1	2,1,0	77.00	48.84	36.10	7.95
0,2,1	1,0,2	81.34	48.84	40.43	7.93
0,2,1	1,1,1	78.76	48.84	35.87	5.95
0,2,1	1,2,0	76.23	48.84	31.32	3.93
0,2,1	0,0,3	79.10	48.84	40.16	9.89
0,2,1	0,1,2	70.63	48.84	35.64	13.85
0,2,1	0,2,1	64.10	48.84	31.09	15.82
0,2,1	0,3,0	59.41	48.84	26.50	15.93
0,3,0	3,0,0	89.65	48.81	40.88	0.05
0,3,0	2,0,1	79.52	48.81	40.66	9.94
0,3,0	2,1,0	76.97	48.81	36.10	7.95
0,3,0	1,0,2	81.31	48.81	40.43	7.93
0,3,0	1,1,1	78.73	48.81	35.87	5.95
0,3,0	1,2,0	76.20	48.81	31.32	3.93
0,3,0	0,0,3	79.08	48.81	40.16	9.89
0,3,0	0,1,2	70.60	48.81	35.64	13.85
0,3,0	0,2,1	64.07	48.81	31.09	15.82
0,3,0	0,3,0	59.38	48.81	26.50	15.93

Five vehicles:

Allocation: Period 1	Allocation: Period 2	Total Revenue	Revenue: Period 1	Revenue: Period 2	Realloc. Cost
5,0,0	5,0,0	79.43	35.03	44.50	0.10
5,0,0	4,0,1	69.28	35.03	47.25	13.00
5,0,0	4,1,0	66.03	35.03	44.50	13.50
5,0,0	3,0,2	70.02	35.03	49.98	15.00
5,0,0	3,1,1	66.48	35.03	45.43	13.99
5,0,0	3,2,0	63.95	35.03	40.87	11.96
5,0,0	2,0,3	68.62	35.03	47.50	13.92
5,0,0	2,1,2	69.24	35.03	45.20	11.00
5,0,0	2,2,1	65.72	35.03	40.64	9.96

5,0,0	2,3,0	63.18	35.03	36.07	7.92
5,0,0	1,0,4	68.15	35.03	45.00	11.88
5,0,0	1,1,3	72.01	35.03	44.97	8.00
5,0,0	1,2,2	67.49	35.03	40.41	7.96
5,0,0	1,3,1	64.95	35.03	35.84	5.93
5,0,0	1,4,0	62.40	35.03	31.25	3.88
5,0,0	0,0,5	63.73	35.03	42.50	13.81
5,0,0	0,1,4	72.53	35.03	42.50	5.00
5,0,0	0,2,3	70.22	35.03	40.18	5.00
5,0,0	0,3,2	61.67	35.03	35.61	8.98
5,0,0	0,4,1	55.12	35.03	31.02	10.93
5,0,0	0,5,0	57.09	35.03	33.20	11.15
4,0,1	5,0,0	83.98	39.64	44.50	0.16
4,0,1	4,0,1	73.89	39.64	47.25	13.00
4,0,1	4,1,0	70.64	39.64	44.50	13.50
4,0,1	3,0,2	74.63	39.64	49.98	15.00
4,0,1	3,1,1	71.08	39.64	45.43	13.99
4,0,1	3,2,0	68.55	39.64	40.87	11.96
4,0,1	2,0,3	73.23	39.64	47.50	13.92
4,0,1	2,1,2	73.84	39.64	45.20	11.00
4,0,1	2,2,1	70.33	39.64	40.64	9.96
4,0,1	2,3,0	67.79	39.64	36.07	7.92
4,0,1	1,0,4	72.76	39.64	45.00	11.88
4,0,1	1,1,3	76.61	39.64	44.97	8.00
4,0,1	1,2,2	72.10	39.64	40.41	7.96
4,0,1	1,3,1	69.55	39.64	35.84	5.92
4,0,1	1,4,0	67.01	39.64	31.25	3.88
4,0,1	0,0,5	68.33	39.64	42.50	13.81
4,0,1	0,1,4	77.14	39.64	42.50	5.00
4,0,1	0,2,3	74.83	39.64	40.18	5.00
4,0,1	0,3,2	66.28	39.64	35.61	8.97
4,0,1	0,4,1	59.73	39.64	31.02	10.93
4,0,1	0,5,0	61.70	39.64	33.20	11.15
4,1,0	5,0,0	83.86	39.56	44.50	0.20
4,1,0	4,0,1	73.81	39.56	47.25	13.00
4,1,0	4,1,0	70.56	39.56	44.50	13.50

4,1,0	3,0,2	74.54	39.56	49.98	15.00
4,1,0	3,1,1	71.00	39.56	45.43	13.99
4,1,0	3,2,0	68.47	39.56	40.87	11.96
4,1,0	2,0,3	73.14	39.56	47.50	13.92
4,1,0	2,1,2	73.76	39.56	45.20	11.00
4,1,0	2,2,1	70.24	39.56	40.64	9.96
4,1,0	2,3,0	67.71	39.56	36.07	7.92
4,1,0	1,0,4	72.67	39.56	45.00	11.88
4,1,0	1,1,3	76.53	39.56	44.97	8.00
4,1,0	1,2,2	72.01	39.56	40.41	7.96
4,1,0	1,3,1	69.47	39.56	35.84	5.93
4,1,0	1,4,0	66.92	39.56	31.25	3.88
4,1,0	0,0,5	68.25	39.56	42.50	13.81
4,1,0	0,1,4	77.06	39.56	42.50	5.00
4,1,0	0,2,3	74.74	39.56	40.18	5.00
4,1,0	0,3,2	66.20	39.56	35.61	8.97
4,1,0	0,4,1	59.64	39.56	31.02	10.93
4,1,0	0,5,0	61.61	39.56	33.20	11.15
3,0,2	5,0,0	88.75	44.33	44.50	0.09
3,0,2	4,0,1	78.58	44.33	47.25	13.00
3,0,2	4,1,0	75.33	44.33	44.50	13.50
3,0,2	3,0,2	79.32	44.33	49.98	15.00
3,0,2	3,1,1	75.78	44.33	45.43	13.99
3,0,2	3,2,0	73.25	44.33	40.87	11.96
3,0,2	2,0,3	77.92	44.33	47.50	13.92
3,0,2	2,1,2	78.54	44.33	45.20	11.00
3,0,2	2,2,1	75.02	44.33	40.64	9.96
3,0,2	2,3,0	72.48	44.33	36.07	7.92
3,0,2	1,0,4	77.45	44.33	45.00	11.88
3,0,2	1,1,3	81.31	44.33	44.97	8.00
3,0,2	1,2,2	76.79	44.33	40.41	7.96
3,0,2	1,3,1	74.25	44.33	35.84	5.92
3,0,2	1,4,0	71.70	44.33	31.25	3.88
3,0,2	0,0,5	73.02	44.33	42.50	13.81
3,0,2	0,1,4	81.83	44.33	42.50	5.00
3,0,2	0,2,3	79.52	44.33	40.18	5.00

3,0,2	0,3,2	70.97	44.33	35.61	8.97
3,0,2	0,4,1	64.42	44.33	31.02	10.93
3,0,2	0,5,0	66.39	44.33	33.20	11.15
3,1,1	5,0,0	88.67	44.26	44.50	0.10
3,1,1	4,0,1	78.52	44.26	47.25	13.00
3,1,1	4,1,0	75.26	44.26	44.50	13.50
3,1,1	3,0,2	79.25	44.26	49.98	15.00
3,1,1	3,1,1	75.70	44.26	45.43	13.99
3,1,1	3,2,0	73.18	44.26	40.87	11.96
3,1,1	2,0,3	77.85	44.26	47.50	13.92
3,1,1	2,1,2	78.46	44.26	45.20	11.00
3,1,1	2,2,1	74.95	44.26	40.64	9.96
3,1,1	2,3,0	72.41	44.26	36.07	7.92
3,1,1	1,0,4	77.38	44.26	45.00	11.88
3,1,1	1,1,3	81.23	44.26	44.97	8.00
3,1,1	1,2,2	76.72	44.26	40.41	7.96
3,1,1	1,3,1	74.18	44.26	35.84	5.93
3,1,1	1,4,0	71.63	44.26	31.25	3.88
3,1,1	0,0,5	72.95	44.26	42.50	13.81
3,1,1	0,1,4	81.76	44.26	42.50	5.00
3,1,1	0,2,3	79.45	44.26	40.18	5.00
3,1,1	0,3,2	70.90	44.26	35.61	8.97
3,1,1	0,4,1	64.35	44.26	31.02	10.93
3,1,1	0,5,0	66.32	44.26	33.20	11.15
3,2,0	5,0,0	88.59	44.19	44.50	0.11
3,2,0	4,0,1	78.44	44.19	47.25	13.00
3,2,0	4,1,0	75.19	44.19	44.50	13.50
3,2,0	3,0,2	79.18	44.19	49.98	15.00
3,2,0	3,1,1	75.63	44.19	45.43	13.99
3,2,0	3,2,0	73.10	44.19	40.87	11.96
3,2,0	2,0,3	77.78	44.19	47.50	13.92
3,2,0	2,1,2	78.39	44.19	45.20	11.00
3,2,0	2,2,1	74.88	44.19	40.64	9.96
3,2,0	2,3,0	72.34	44.19	36.07	7.92
3,2,0	1,0,4	77.31	44.19	45.00	11.88
3,2,0	1,1,3	81.16	44.19	44.97	8.00

3,2,0	1,2,2	76.65	44.19	40.41	7.96
3,2,0	1,3,1	74.11	44.19	35.84	5.93
3,2,0	1,4,0	71.56	44.19	31.25	3.88
3,2,0	0,0,5	72.88	44.19	42.50	13.81
3,2,0	0,1,4	81.69	44.19	42.50	5.00
3,2,0	0,2,3	79.38	44.19	40.18	5.00
3,2,0	0,3,2	70.83	44.19	35.61	8.97
3,2,0	0,4,1	64.28	44.19	31.02	10.93
3,2,0	0,5,0	66.25	44.19	33.20	11.15
2,0,3	5,0,0	92.06	48.00	44.50	0.44
2,0,3	4,0,1	82.25	48.00	47.25	13.00
2,0,3	4,1,0	79.00	48.00	44.50	13.50
2,0,3	3,0,2	82.98	48.00	49.98	15.00
2,0,3	3,1,1	79.44	48.00	45.43	13.99
2,0,3	3,2,0	76.91	48.00	40.87	11.96
2,0,3	2,0,3	81.58	48.00	47.50	13.92
2,0,3	2,1,2	82.20	48.00	45.20	11.00
2,0,3	2,2,1	78.68	48.00	40.64	9.96
2,0,3	2,3,0	76.15	48.00	36.07	7.92
2,0,3	1,0,4	81.12	48.00	45.00	11.88
2,0,3	1,1,3	84.97	48.00	44.97	8.00
2,0,3	1,2,2	80.45	48.00	40.41	7.96
2,0,3	1,3,1	77.91	48.00	35.84	5.93
2,0,3	1,4,0	75.37	48.00	31.25	3.88
2,0,3	0,0,5	76.69	48.00	42.50	13.81
2,0,3	0,1,4	85.50	48.00	42.50	5.00
2,0,3	0,2,3	83.18	48.00	40.18	5.00
2,0,3	0,3,2	74.64	48.00	35.61	8.97
2,0,3	0,4,1	68.09	48.00	31.02	10.93
2,0,3	0,5,0	70.05	48.00	33.20	11.15
2,1,2	5,0,0	93.27	48.89	44.50	0.12
2,1,2	4,0,1	83.14	48.89	47.25	13.00
2,1,2	4,1,0	79.89	48.89	44.50	13.50
2,1,2	3,0,2	83.88	48.89	49.98	15.00
2,1,2	3,1,1	80.34	48.89	45.43	13.99
2,1,2	3,2,0	77.81	48.89	40.87	11.96

2,1,2	2,0,3	82.48	48.89	47.50	13.92
2,1,2	2,1,2	83.10	48.89	45.20	11.00
2,1,2	2,2,1	79.58	48.89	40.64	9.96
2,1,2	2,3,0	77.04	48.89	36.07	7.92
2,1,2	1,0,4	82.01	48.89	45.00	11.88
2,1,2	1,1,3	85.87	48.89	44.97	8.00
2,1,2	1,2,2	81.35	48.89	40.41	7.96
2,1,2	1,3,1	78.81	48.89	35.84	5.93
2,1,2	1,4,0	76.26	48.89	31.25	3.88
2,1,2	0,0,5	77.58	48.89	42.50	13.81
2,1,2	0,1,4	86.39	48.89	42.50	5.00
2,1,2	0,2,3	84.08	48.89	40.18	5.00
2,1,2	0,3,2	75.53	48.89	35.61	8.97
2,1,2	0,4,1	68.98	48.89	31.02	10.93
2,1,2	0,5,0	70.95	48.89	33.20	11.15
2,2,1	5,0,0	93.32	48.87	44.50	0.05
2,2,1	4,0,1	83.12	48.87	47.25	13.00
2,2,1	4,1,0	79.87	48.87	44.50	13.50
2,2,1	3,0,2	83.86	48.87	49.98	15.00
2,2,1	3,1,1	80.31	48.87	45.43	13.99
2,2,1	3,2,0	77.78	48.87	40.87	11.96
2,2,1	2,0,3	82.46	48.87	47.50	13.92
2,2,1	2,1,2	83.07	48.87	45.20	11.00
2,2,1	2,2,1	79.56	48.87	40.64	9.96
2,2,1	2,3,0	77.02	48.87	36.07	7.92
2,2,1	1,0,4	81.99	48.87	45.00	11.88
2,2,1	1,1,3	85.84	48.87	44.97	8.00
2,2,1	1,2,2	81.33	48.87	40.41	7.96
2,2,1	1,3,1	78.79	48.87	35.84	5.93
2,2,1	1,4,0	76.24	48.87	31.25	3.88
2,2,1	0,0,5	77.56	48.87	42.50	13.81
2,2,1	0,1,4	86.37	48.87	42.50	5.00
2,2,1	0,2,3	84.06	48.87	40.18	5.00
2,2,1	0,3,2	75.51	48.87	35.61	8.97
2,2,1	0,4,1	68.96	48.87	31.02	10.93
2,2,1	0,5,0	70.93	48.87	33.20	11.15

2,3,0	5,0,0	93.25	48.81	44.50	0.05
2,3,0	4,0,1	83.06	48.81	47.25	13.00
2,3,0	4,1,0	79.81	48.81	44.50	13.50
2,3,0	3,0,2	83.79	48.81	49.98	15.00
2,3,0	3,1,1	80.25	48.81	45.43	13.99
2,3,0	3,2,0	77.72	48.81	40.87	11.96
2,3,0	2,0,3	82.39	48.81	47.50	13.91
2,3,0	2,1,2	83.01	48.81	45.20	11.00
2,3,0	2,2,1	79.49	48.81	40.64	9.96
2,3,0	2,3,0	76.95	48.81	36.07	7.92
2,3,0	1,0,4	81.92	48.81	45.00	11.88
2,3,0	1,1,3	85.78	48.81	44.97	8.00
2,3,0	1,2,2	81.26	48.81	40.41	7.96
2,3,0	1,3,1	78.72	48.81	35.84	5.93
2,3,0	1,4,0	76.17	48.81	31.25	3.88
2,3,0	0,0,5	77.50	48.81	42.50	13.81
2,3,0	0,1,4	86.31	48.81	42.50	5.00
2,3,0	0,2,3	83.99	48.81	40.18	5.00
2,3,0	0,3,2	75.44	48.81	35.61	8.97
2,3,0	0,4,1	68.89	48.81	31.02	10.93
2,3,0	0,5,0	70.86	48.81	33.20	11.15
1,0,4	5,0,0	90.06	48.00	44.50	2.44
1,0,4	4,0,1	82.25	48.00	47.25	13.00
1,0,4	4,1,0	79.00	48.00	44.50	13.50
1,0,4	3,0,2	82.98	48.00	49.98	15.00
1,0,4	3,1,1	79.44	48.00	45.43	13.99
1,0,4	3,2,0	76.91	48.00	40.87	11.96
1,0,4	2,0,3	81.58	48.00	47.50	13.92
1,0,4	2,1,2	82.20	48.00	45.20	11.00
1,0,4	2,2,1	78.68	48.00	40.64	9.96
1,0,4	2,3,0	76.15	48.00	36.07	7.92
1,0,4	1,0,4	81.12	48.00	45.00	11.88
1,0,4	1,1,3	84.97	48.00	44.97	8.00
1,0,4	1,2,2	80.45	48.00	40.41	7.96
1,0,4	1,3,1	77.91	48.00	35.84	5.93
1,0,4	1,4,0	75.37	48.00	31.25	3.88

1,0,4	0,0,5	76.69	48.00	42.50	13.81
1,0,4	0,1,4	85.50	48.00	42.50	5.00
1,0,4	0,2,3	83.18	48.00	40.18	5.00
1,0,4	0,3,2	74.64	48.00	35.61	8.97
1,0,4	0,4,1	68.09	48.00	31.02	10.93
1,0,4	0,5,0	70.05	48.00	33.20	11.15
1,1,3	5,0,0	92.91	50.00	44.50	1.59
1,1,3	4,0,1	84.25	50.00	47.25	13.00
1,1,3	4,1,0	81.00	50.00	44.50	13.50
1,1,3	3,0,2	84.98	50.00	49.98	15.00
1,1,3	3,1,1	81.44	50.00	45.43	13.99
1,1,3	3,2,0	78.91	50.00	40.87	11.96
1,1,3	2,0,3	83.58	50.00	47.50	13.92
1,1,3	2,1,2	84.20	50.00	45.20	11.00
1,1,3	2,2,1	80.68	50.00	40.64	9.96
1,1,3	2,3,0	78.15	50.00	36.07	7.92
1,1,3	1,0,4	83.12	50.00	45.00	11.88
1,1,3	1,1,3	86.97	50.00	44.97	8.00
1,1,3	1,2,2	82.45	50.00	40.41	7.96
1,1,3	1,3,1	79.92	50.00	35.84	5.93
1,1,3	1,4,0	77.37	50.00	31.25	3.88
1,1,3	0,0,5	78.69	50.00	42.50	13.81
1,1,3	0,1,4	87.50	50.00	42.50	5.00
1,1,3	0,2,3	85.18	50.00	40.18	5.00
1,1,3	0,3,2	76.64	50.00	35.61	8.97
1,1,3	0,4,1	70.09	50.00	31.02	10.93
1,1,3	0,5,0	72.05	50.00	33.20	11.15
1,2,2	5,0,0	95.83	52.00	44.50	0.67
1,2,2	4,0,1	86.25	52.00	47.25	13.00
1,2,2	4,1,0	83.00	52.00	44.50	13.50
1,2,2	3,0,2	86.98	52.00	49.98	15.00
1,2,2	3,1,1	83.44	52.00	45.43	13.99
1,2,2	3,2,0	80.91	52.00	40.87	11.96
1,2,2	2,0,3	85.58	52.00	47.50	13.92
1,2,2	2,1,2	86.20	52.00	45.20	11.00
1,2,2	2,2,1	82.68	52.00	40.64	9.96

1,2,2	2,3,0	80.15	52.00	36.07	7.92
1,2,2	1,0,4	85.12	52.00	45.00	11.88
1,2,2	1,1,3	88.97	52.00	44.97	8.00
1,2,2	1,2,2	84.45	52.00	40.41	7.96
1,2,2	1,3,1	81.91	52.00	35.84	5.93
1,2,2	1,4,0	79.37	52.00	31.25	3.88
1,2,2	0,0,5	80.69	52.00	42.50	13.81
1,2,2	0,1,4	89.50	52.00	42.50	5.00
1,2,2	0,2,3	87.18	52.00	40.18	5.00
1,2,2	0,3,2	78.64	52.00	35.61	8.97
1,2,2	0,4,1	72.09	52.00	31.02	10.93
1,2,2	0,5,0	74.05	52.00	33.20	11.15
1,3,1	5,0,0	97.88	53.45	44.50	0.06
1,3,1	4,0,1	87.70	53.45	47.25	13.00
1,3,1	4,1,0	84.45	53.45	44.50	13.50
1,3,1	3,0,2	88.43	53.45	49.98	15.00
1,3,1	3,1,1	84.89	53.45	45.43	13.99
1,3,1	3,2,0	82.36	53.45	40.87	11.96
1,3,1	2,0,3	87.03	53.45	47.50	13.92
1,3,1	2,1,2	87.65	53.45	45.20	11.00
1,3,1	2,2,1	84.13	53.45	40.64	9.96
1,3,1	2,3,0	81.59	53.45	36.07	7.92
1,3,1	1,0,4	86.56	53.45	45.00	11.88
1,3,1	1,1,3	90.42	53.45	44.97	8.00
1,3,1	1,2,2	85.90	53.45	40.41	7.96
1,3,1	1,3,1	83.36	53.45	35.84	5.93
1,3,1	1,4,0	80.81	53.45	31.25	3.88
1,3,1	0,0,5	82.14	53.45	42.50	13.81
1,3,1	0,1,4	90.95	53.45	42.50	5.00
1,3,1	0,2,3	88.63	53.45	40.18	5.00
1,3,1	0,3,2	80.08	53.45	35.61	8.97
1,3,1	0,4,1	73.53	53.45	31.02	10.93
1,3,1	0,5,0	75.50	53.45	33.20	11.15
1,4,0	5,0,0	97.88	53.40	44.50	0.02
1,4,0	4,0,1	87.65	53.40	47.25	13.00
1,4,0	4,1,0	84.40	53.40	44.50	13.50

1,4,0	3,0,2	88.39	53.40	49.98	15.00
1,4,0	3,1,1	84.85	53.40	45.43	13.99
1,4,0	3,2,0	82.32	53.40	40.87	11.96
1,4,0	2,0,3	86.99	53.40	47.50	13.92
1,4,0	2,1,2	87.61	53.40	45.20	11.00
1,4,0	2,2,1	84.09	53.40	40.64	9.96
1,4,0	2,3,0	81.55	53.40	36.07	7.92
1,4,0	1,0,4	86.52	53.40	45.00	11.88
1,4,0	1,1,3	90.38	53.40	44.97	8.00
1,4,0	1,2,2	85.86	53.40	40.41	7.96
1,4,0	1,3,1	83.32	53.40	35.84	5.93
1,4,0	1,4,0	80.77	53.40	31.25	3.88
1,4,0	0,0,5	82.09	53.40	42.50	13.81
1,4,0	0,1,4	90.90	53.40	42.50	5.00
1,4,0	0,2,3	88.59	53.40	40.18	5.00
1,4,0	0,3,2	80.04	53.40	35.61	8.97
1,4,0	0,4,1	73.49	53.40	31.02	10.93
1,4,0	0,5,0	75.46	53.40	33.20	11.15
0,0,5	5,0,0	88.06	48.00	44.50	4.44
0,0,5	4,0,1	82.25	48.00	47.25	13.00
0,0,5	4,1,0	79.00	48.00	44.50	13.50
0,0,5	3,0,2	82.98	48.00	49.98	15.00
0,0,5	3,1,1	79.44	48.00	45.43	13.99
0,0,5	3,2,0	76.91	48.00	40.87	11.96
0,0,5	2,0,3	81.58	48.00	47.50	13.92
0,0,5	2,1,2	82.20	48.00	45.20	11.00
0,0,5	2,2,1	78.68	48.00	40.64	9.96
0,0,5	2,3,0	76.15	48.00	36.07	7.92
0,0,5	1,0,4	81.12	48.00	45.00	11.88
0,0,5	1,1,3	84.97	48.00	44.97	8.00
0,0,5	1,2,2	80.45	48.00	40.41	7.96
0,0,5	1,3,1	77.91	48.00	35.84	5.93
0,0,5	1,4,0	75.37	48.00	31.25	3.88
0,0,5	0,0,5	80.57	48.00	42.50	9.93
0,0,5	0,1,4	85.50	48.00	42.50	5.00
0,0,5	0,2,3	83.18	48.00	40.18	5.00
0,0,5	0,3,2	79.64	48.00	35.61	3.97
0,0,5	0,4,1	77.06	48.00	31.02	1.96

0,0,5	0,5,0	80.99	48.00	33.20	0.22
0,1,4	5,0,0	90.94	50.00	44.50	3.56
0,1,4	4,0,1	84.25	50.00	47.25	13.00
0,1,4	4,1,0	81.00	50.00	44.50	13.50
0,1,4	3,0,2	84.98	50.00	49.98	15.00
0,1,4	3,1,1	81.44	50.00	45.43	13.99
0,1,4	3,2,0	78.91	50.00	40.87	11.96
0,1,4	2,0,3	83.58	50.00	47.50	13.92
0,1,4	2,1,2	84.20	50.00	45.20	11.00
0,1,4	2,2,1	80.68	50.00	40.64	9.96
0,1,4	2,3,0	78.15	50.00	36.07	7.92
0,1,4	1,0,4	83.12	50.00	45.00	11.88
0,1,4	1,1,3	86.97	50.00	44.97	8.00
0,1,4	1,2,2	82.45	50.00	40.41	7.96
0,1,4	1,3,1	79.91	50.00	35.84	5.93
0,1,4	1,4,0	77.37	50.00	31.25	3.88
0,1,4	0,0,5	82.57	50.00	42.50	9.93
0,1,4	0,1,4	87.50	50.00	42.50	5.00
0,1,4	0,2,3	85.18	50.00	40.18	5.00
0,1,4	0,3,2	81.64	50.00	35.61	3.97
0,1,4	0,4,1	79.06	50.00	31.02	1.96
0,1,4	0,5,0	82.99	50.00	33.20	0.22
0,2,3	5,0,0	93.81	52.00	44.50	2.69
0,2,3	4,0,1	86.25	52.00	47.25	13.00
0,2,3	4,1,0	83.00	52.00	44.50	13.50
0,2,3	3,0,2	86.98	52.00	49.98	15.00
0,2,3	3,1,1	83.44	52.00	45.43	13.99
0,2,3	3,2,0	80.92	52.00	40.87	11.96
0,2,3	2,0,3	85.59	52.00	47.50	13.92
0,2,3	2,1,2	86.20	52.00	45.20	11.00
0,2,3	2,2,1	82.68	52.00	40.64	9.96
0,2,3	2,3,0	80.15	52.00	36.07	7.92
0,2,3	1,0,4	85.12	52.00	45.00	11.88
0,2,3	1,1,3	88.97	52.00	44.97	8.00
0,2,3	1,2,2	84.45	52.00	40.41	7.96
0,2,3	1,3,1	81.91	52.00	35.84	5.93
0,2,3	1,4,0	79.37	52.00	31.25	3.88
0,2,3	0,0,5	84.57	52.00	42.50	9.93
0,2,3	0,1,4	89.50	52.00	42.50	5.00

0,2,3	0,2,3	87.18	52.00	40.18	5.00
0,2,3	0,3,2	83.64	52.00	35.61	3.97
0,2,3	0,4,1	81.06	52.00	31.02	1.96
0,2,3	0,5,0	84.99	52.00	33.20	0.22
0,3,2	5,0,0	96.72	54.00	44.50	1.78
0,3,2	4,0,1	88.25	54.00	47.25	13.00
0,3,2	4,1,0	85.00	54.00	44.50	13.50
0,3,2	3,0,2	88.98	54.00	49.98	15.00
0,3,2	3,1,1	85.44	54.00	45.43	13.99
0,3,2	3,2,0	82.91	54.00	40.87	11.96
0,3,2	2,0,3	87.58	54.00	47.50	13.92
0,3,2	2,1,2	88.20	54.00	45.20	11.00
0,3,2	2,2,1	84.68	54.00	40.64	9.96
0,3,2	2,3,0	82.15	54.00	36.07	7.92
0,3,2	1,0,4	87.12	54.00	45.00	11.88
0,3,2	1,1,3	90.97	54.00	44.97	8.00
0,3,2	1,2,2	86.45	54.00	40.41	7.96
0,3,2	1,3,1	83.91	54.00	35.84	5.93
0,3,2	1,4,0	81.37	54.00	31.25	3.88
0,3,2	0,0,5	86.57	54.00	42.50	9.93
0,3,2	0,1,4	91.50	54.00	42.50	5.00
0,3,2	0,2,3	89.18	54.00	40.18	5.00
0,3,2	0,3,2	85.64	54.00	35.61	3.97
0,3,2	0,4,1	83.06	54.00	31.02	1.96
0,3,2	0,5,0	86.99	54.00	33.20	0.22
0,4,1	5,0,0	99.61	56.00	44.50	0.89
0,4,1	4,0,1	90.25	56.00	47.25	13.00
0,4,1	4,1,0	87.00	56.00	44.50	13.50
0,4,1	3,0,2	90.98	56.00	49.98	15.00
0,4,1	3,1,1	87.44	56.00	45.43	13.99
0,4,1	3,2,0	84.91	56.00	40.87	11.96
0,4,1	2,0,3	89.58	56.00	47.50	13.92
0,4,1	2,1,2	90.20	56.00	45.20	11.00
0,4,1	2,2,1	86.68	56.00	40.64	9.96
0,4,1	2,3,0	84.15	56.00	36.07	7.92
0,4,1	1,0,4	89.12	56.00	45.00	11.88
0,4,1	1,1,3	92.97	56.00	44.97	8.00
0,4,1	1,2,2	88.45	56.00	40.41	7.96
0,4,1	1,3,1	85.91	56.00	35.84	5.93

0,4,1	1,4,0	83.37	56.00	31.25	3.88
0,4,1	0,0,5	88.57	56.00	42.50	9.93
0,4,1	0,1,4	93.50	56.00	42.50	5.00
0,4,1	0,2,3	91.18	56.00	40.18	5.00
0,4,1	0,3,2	87.64	56.00	35.61	3.97
0,4,1	0,4,1	85.06	56.00	31.02	1.96
0,4,1	0,5,0	88.97	56.00	33.20	0.22
0,5,0	5,0,0	102.46	57.98	44.50	0.01
0,5,0	4,0,1	92.23	57.98	47.25	13.00
0,5,0	4,1,0	88.97	57.98	44.50	13.50
0,5,0	3,0,2	92.96	57.98	49.98	15.00
0,5,0	3,1,1	89.42	57.98	45.43	13.99
0,5,0	3,2,0	86.89	57.98	40.87	11.96
0,5,0	2,0,3	91.56	57.98	47.50	13.92
0,5,0	2,1,2	92.18	57.98	45.20	11.00
0,5,0	2,2,1	88.65	57.98	40.64	9.96
0,5,0	2,3,0	86.13	57.98	36.07	7.92
0,5,0	1,0,4	91.09	57.98	45.00	11.88
0,5,0	1,1,3	94.95	57.98	44.97	8.00
0,5,0	1,2,2	90.43	57.98	40.41	7.96
0,5,0	1,3,1	87.89	57.98	35.84	5.93
0,5,0	1,4,0	85.34	57.98	31.25	3.88
0,5,0	0,0,5	90.55	57.98	42.50	9.92
0,5,0	0,1,4	95.48	57.98	42.50	5.00
0,5,0	0,2,3	93.16	57.98	40.18	5.00
0,5,0	0,3,2	89.62	57.98	35.61	3.97
0,5,0	0,4,1	87.03	57.98	31.02	1.96
0,5,0	0,5,0	90.96	57.98	33.20	0.22

Appendix C: Twenty Zone Allocation Model Inputs

Period One Demand

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Total
1	24	9	4	12	66	49	17	7	13	18	11	61	49	3	5	18	29	0	19	9	423
2	23	11	3	18	8	30	22	11	1	4	14	10	10	5	2	12	7	5	13	30	239
3	19	13	1	50	46	46	21	36	3	8	39	6	28	0	2	7	10	3	11	4	353
4	11	11	0	5	6	16	8	11	13	3	5	7	19	2	0	1	1	1	8	1	129
5	4	3	1	3	2	8	3	5	4	2	3	11	10	0	0	2	6	1	1	0	69
6	5	3	0	5	17	14	7	4	7	4	15	11	7	1	0	3	14	2	1	7	127
7	17	19	0	21	47	2	2	21	16	1	21	11	4	6	0	3	33	5	6	35	270
8	9	2	1	25	23	1	8	6	8	7	4	14	15	0	0	2	23	1	6	8	163
9	2	0	0	1	4	7	3	2	3	0	4	6	6	0	0	1	5	0	1	0	45
10	13	28	4	27	63	33	29	52	29	17	35	51	27	5	2	13	54	7	21	5	515
11	0	0	0	1	0	1	0	1	0	0	1	0	1	0	0	0	1	0	0	1	7
12	8	22	2	33	17	69	7	24	33	17	28	29	72	4	7	10	16	3	18	42	461
13	8	21	3	30	28	16	16	6	14	8	39	24	5	4	2	5	23	4	13	5	274
14	19	7	1	25	11	39	3	4	21	14	36	25	18	5	2	5	27	4	7	17	290
15	11	7	1	12	1	17	7	9	8	11	25	12	24	3	1	6	20	2	6	18	201
16	1	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	4
17	18	27	3	53	47	59	9	45	23	26	49	55	27	7	4	5	4	2	11	21	495
18	3	0	0	4	5	6	3	4	2	0	0	4	3	1	0	2	0	0	0	0	37
19	3	3	0	11	13	3	1	7	0	1	12	2	10	1	1	4	5	1	5	6	89
20	21	12	3	21	8	28	4	9	18	6	6	17	3	6	1	1	10	2	4	2	182
Total	219	198	27	357	412	445	170	264	216	148	348	356	338	53	29	100	288	43	151	211	4253

Period Two Demand

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Total
1	18	6	8	15	20	42	10	66	15	1	34	0	0	2	14	8	24	20	30	31	364
2	21	3	1	3	4	17	1	12	4	5	7	1	0	7	11	6	1	9	12	5	130
3	43	13	3	6	6	18	1	36	13	4	32	2	0	11	28	26	25	22	5	30	324
4	11	10	5	8	10	2	4	32	3	2	10	0	0	20	13	11	5	18	12	25	201
5	38	7	0	28	4	26	2	56	8	9	30	2	0	21	28	7	1	1	10	3	281
6	22	4	2	6	11	10	10	18	5	1	8	1	1	10	15	15	8	1	14	25	187
7	13	2	1	1	7	8	0	6	3	2	6	0	0	7	4	5	2	4	6	17	94
8	25	5	6	2	6	17	2	46	2	3	14	1	0	10	3	0	16	15	1	3	177
9	2	1	0	1	0	0	1	3	0	0	0	0	0	2	1	0	0	1	0	1	13
10	23	19	1	37	17	10	2	15	1	11	26	3	0	42	10	6	2	8	18	80	331
11	7	2	0	3	2	5	1	3	1	1	3	0	0	3	4	1	0	3	3	9	51
12	26	1	2	16	5	30	6	10	4	4	12	1	0	18	1	11	9	18	5	25	204
13	10	0	10	13	18	10	7	6	10	6	6	1	0	18	2	18	10	18	6	1	170
14	32	0	12	11	6	31	7	9	7	1	15	1	0	3	8	3	3	9	9	38	205
15	7	5	2	7	5	4	1	4	2	3	3	0	0	5	1	0	7	4	6	5	71
16	6	10	9	4	18	14	9	47	2	4	8	0	1	18	11	3	11	4	1	45	225
17	23	8	10	7	5	18	3	48	9	4	18	0	1	18	13	5	3	21	22	38	274
18	0	11	1	21	12	18	9	29	4	7	10	1	0	22	5	1	16	4	8	17	196
19	22	9	2	1	8	34	15	57	3	1	0	3	1	23	24	16	23	10	11	71	334
20	2	1	1	1	2	2	1	3	0	0	1	0	0	1	0	2	2	2	1	1	23
Total	351	117	76	191	166	316	92	506	96	69	243	17	4	261	196	144	168	192	180	470	3855

Travel and Reallocation Time/Cost Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.28	0.58	0.18	0.53	0.99	0.18	0.19	0.26	0.70	0.24	0.64	0.85	0.52	0.30	0.91	0.60	0.37	0.96	0.69	0.95
2	0.63	0.82	0.24	0.06	0.39	0.45	0.17	0.56	0.51	0.48	0.83	0.95	0.33	0.50	0.60	0.64	0.29	0.11	0.59	0.80
3	0.33	0.52	0.85	0.24	0.76	0.56	0.37	0.68	0.67	0.79	0.32	0.19	0.70	0.85	0.50	0.93	0.45	0.97	0.78	0.07
4	0.97	0.07	0.11	0.56	0.83	0.44	0.44	0.12	0.21	0.22	0.97	0.42	0.54	0.94	0.57	0.39	0.37	0.06	0.56	0.73
5	0.34	0.42	0.16	0.38	0.68	0.10	1.00	0.86	0.05	0.62	0.24	0.98	0.10	0.50	0.56	0.88	0.83	0.98	0.94	0.00
6	0.71	0.21	0.68	0.65	0.74	0.83	0.40	0.28	0.48	0.46	0.48	0.20	0.09	0.59	0.35	0.16	0.92	0.77	0.48	0.97
7	0.12	0.14	0.08	0.43	0.12	0.91	0.01	0.41	0.19	0.55	0.39	0.03	0.58	0.44	0.59	0.49	0.95	0.08	0.07	0.01
8	0.38	0.87	0.51	0.87	0.11	0.51	0.60	0.25	0.89	0.36	0.76	0.67	0.84	0.95	0.87	0.87	0.10	0.75	0.76	0.99
9	0.37	0.37	0.27	0.84	0.37	0.87	0.12	0.25	0.41	0.43	0.40	0.07	0.27	0.04	0.33	0.49	0.16	0.22	0.54	0.58
10	0.20	0.73	0.82	0.73	0.07	0.74	0.09	0.39	0.39	0.61	0.77	0.16	0.78	0.46	0.62	0.09	0.97	0.09	0.14	0.07
11	0.15	0.38	0.41	0.52	0.16	0.03	0.03	0.56	0.01	0.47	0.19	0.90	0.54	0.06	0.40	0.22	0.47	0.84	0.18	0.20
12	0.59	0.22	0.39	0.04	0.34	0.97	0.77	0.27	0.78	0.75	0.69	0.00	0.13	0.37	0.66	0.37	0.17	0.58	0.05	0.33
13	0.79	0.27	0.11	0.49	0.01	0.88	0.31	0.71	0.12	0.18	0.93	0.62	0.82	0.15	0.30	0.36	0.59	0.24	0.64	0.85
14	0.82	0.16	0.84	0.65	0.90	0.90	0.10	0.30	0.16	0.95	0.93	0.85	0.09	0.80	0.10	0.75	0.58	0.11	0.15	0.92
15	0.36	0.88	0.28	0.82	0.69	0.56	0.02	0.45	0.02	0.70	0.78	0.89	0.15	0.00	0.02	0.77	0.06	0.21	0.09	0.91
16	0.01	0.86	0.02	0.23	0.81	0.11	0.82	1.00	0.32	0.24	0.09	0.29	0.78	0.63	0.91	0.83	0.20	0.51	1.00	0.01
17	0.34	0.73	0.19	0.58	0.34	0.64	0.34	0.76	0.03	0.74	0.22	0.37	0.99	0.51	0.81	0.89	0.03	0.60	0.77	0.42
18	0.85	0.30	0.10	0.43	0.12	0.67	0.57	0.56	0.14	0.02	0.15	0.89	0.59	0.87	0.48	0.08	0.04	0.32	0.27	0.56
19	0.09	0.58	0.24	0.64	0.92	0.92	0.32	0.96	0.98	0.92	0.73	0.67	0.48	0.74	0.76	0.76	0.66	0.07	0.11	0.13
20	0.65	0.48	0.81	0.87	0.96	0.56	0.91	0.25	0.83	0.61	0.29	0.27	0.38	0.33	0.06	0.10	0.11	0.55	0.83	0.25

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