Do Variable-Pricing Strategies Influence the Activity-Travel Patterns of Carsharing Users? A Case Study

Sisinnio Concas (Corresponding Author)
concas@cutr.usf.edu

Sean J. Barbeau
barbeau@cutr.usf.edu

Philip L.Winters
winters@cutr.usf.edu

Nevine Labib Georggi
georggi@cutr.usf.edu

Julie Bond
bond@cutr.usf.edu

Center for Urban Transportation Research
University of South Florida
Tampa, FL 33620
813-974-3120 ph
813-9745168 fax

ABSTRACT

Carsharing, a short-term auto rental offering convenience and flexibility, has been shown to decrease reliance on personal vehicle for all types of trips. This paper presents a case study that sought to determine if variable-pricing strategies would influence activity-travel patterns of carsharing users. Using global positioning system-enabled mobile phones, travel behavior data were collected from experimental and control groups in three-week cycles before and after the implementation of pricing strategies. Data-driven nonparametric estimation methods were used to evaluate the impact on area-based geometric measures of spatial dispersion of out-of-home activities in response to changes in hourly rates. Joint probability density function estimates of trips by cost and rental time show that carsharing users' spatial dispersion of trips decreases while using carsharing as a mode of transport. These findings provide evidence that carsharing can help reduce traffic congestion by reducing the spatial and temporal range of travel patterns.

Word Count: 4,038+ 3,500 (14 Tables/Figures) = 7,538

Submitted in Response to Paper Call: " Experimental Economics/Cognitive Psychology and Road Pricing"

Sponsoring Committee: ABE25 Congestion Pricing
Co-Sponsoring Committee: ABE20 Transportation Economics

1. INTRODUCTION

More communities are adopting the use of pricing to help manage congestion and environmental impacts. Their use of high occupancy toll (HOT) lanes and managed lanes provide access to faster travel speeds and more reliable travel times in exchange for a payment or willingness to carry passengers. Other pricing approaches include pay-as-you-drive insurance, variable parking pricing based on demand, and carsharing.

Carsharing is a membership-based service that provides access to a fleet of vehicles rented on a short-term basis with 24/7 access. The rental cost typically covers gas, maintenance and insurance. Members reserve a car online or by phone, access the vehicle with an electronic key card to drive it and then return it to the same location. Carsharing can substitute for car ownership or provide employees access to vehicles for business use or personal errands during the day to avoid driving to work [1]. Research finds that carsharing customers increase their use of carpooling, bicycling and walking, though the impact on transit use shows a slight overall decline [2]. A study of North American carsharing organizations demonstrates how the impact of carsharing on transit depends upon users' travel preferences [3]. As energy price uncertainty increases, carsharing is poised to grow in the near future [4]. As carsharing programs grow, the question of how variable pricing can be applied to influence usage patterns and levels become relevant. Taking trips in the off-peak period reduces congestion thus reducing delay, saving time, and improving air quality.

This paper presents the results of a study funded by the U.S. Department of Transportation Value Pricing Pilot Program that assessed how carsharing use affected travel patterns by comparing the spatial dispersions of trips made by carsharing users and non-users[5]. The research also tested approaches to carsharing pricing which sought to smooth peak-period usage and shift the rental period in time.

The project was situated in a car-centric university setting with limited transit options. GPS-enabled mobile phones with the mobile application TRAC-IT were used to collect travel behavior data for a sample of participants to provide longitudinal information on the program's impacts.

2. IMPLEMENTING THE CARSHARING PROGRAM

The carsharing program was launched on July 23, 2009 at the University of South Florida Tampa campus. Through an agreement with a carsharing vendor, the program started with a fleet of four hybrid vehicles available to students, faculty, and staff. During the project, the vehicle mix changed to meet student preferences or carsharing technology problems. Vehicles were located in pairs at two convenient and visible locations within campus parking lots chosen in proximity of dormitories and the student center.

The first phase of the project focused on building awareness of carsharing and adding new members. The university and the carsharing vendor formed a partnership to effectively introduce and market the program to students, faculty and staff. A variety of marketing outreach techniques were used, including staffing table events on campus, participating in weekly outdoor events, creating and updating a Facebook page, providing materials for residence hall displays, and coordinating advertising.

2.1 Carsharing Membership and Usage

The above approaches helped membership grow steadily with nearly 50 active members per carsharing vehicle by June 2011, considered as the ratio to make the carsharing program sustainable from a business perspective. Vehicle rentals increased at an exponential rate, corresponding to growth in membership, increased awareness and other promotions (Figure 1), totaling 1,852 reservations between September 2009 and May 2011. The monthly variations in membership and usage correspond to the natural fluctuations in a university schedule (e.g., winter break and summer session) and pricing levels.

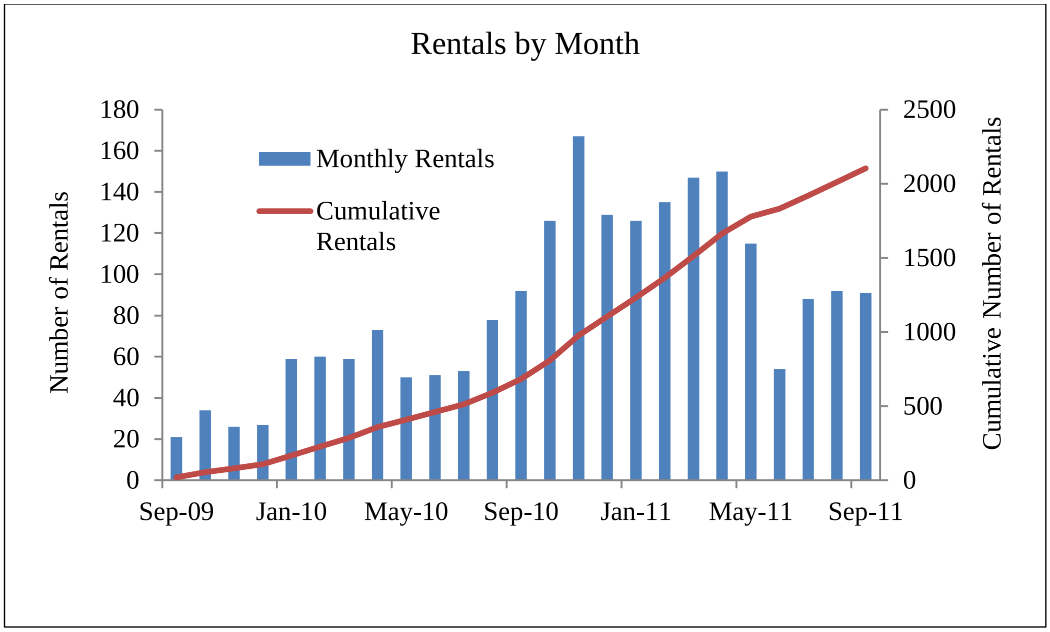

FIGURE 1 Carsharing Rentals

Once the program was established, the next step was to determine when the peak periods of carsharing usage were happening to test pricing strategies that would affect behavior in those peak periods. Monthly revenue and membership reports provided detailed information on date and time for rental reservation and use, vehicle type and location, hourly cost, total rental cost, total rental time and mileage. The use of carsharing gradually increased over the course of the week with usage peaking on Friday and Saturday. The vast majority of carsharing trips occurred in the off-peak periods, rather than traditional rush hour periods. A deeply discounted evening rental beginning at 6 PM was put in place by the carsharing vendor from the beginning, causing the spike in Figure 2.

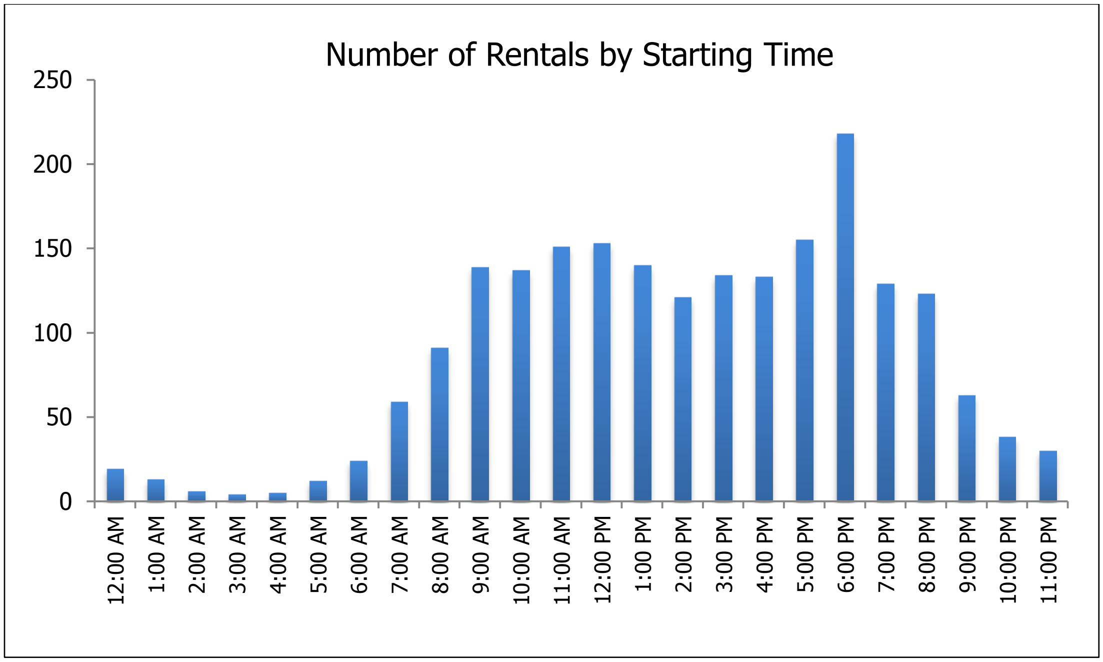

FIGURE 2 Rentals by Start Time

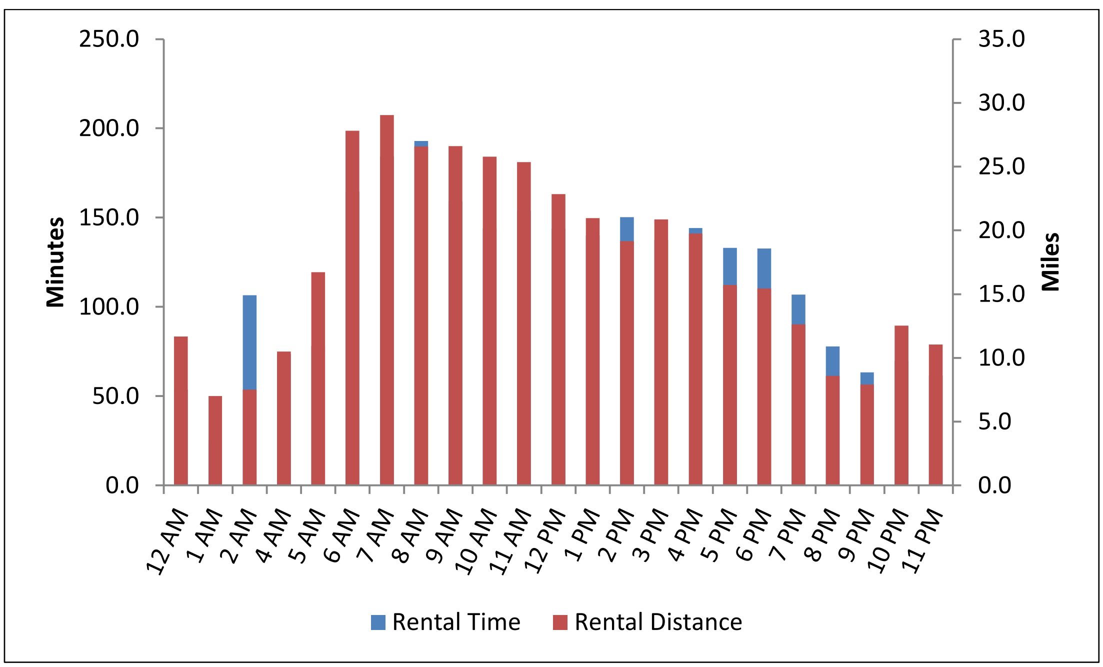

FIGURE 3 Rental Time and Rental Distance

The average weekday trip was 21 miles long and lasts about 140 minutes. Trip length and duration varied by hour of the day, as shown in **Error! Not a valid bookmark self-reference.**. The use of bivariate density estimates in lieu of histograms provide a better appreciation of the underlying structure of trips and rental costs.

A bivariate density distribution of trips by distance and time can reveal how spread rentals are from their point of origin (i.e. car parking lot as campus premises). Given that the marginal distributions do not appear to be members of standard parametric distributions, bivariate kernel density estimation methods, which are capable of providing a more complete picture, are preferred. The interest was in exploring the joint structure of rental cost and distance traveled. The analysis adopted the conventional notation with f (rental distance; rental time) denoting the joint probability density function of the random variables trip cost and distance respectively. As noted above, one could proceed with a parametric approach assuming, for example, that the joint distribution is Gaussian, or normal. However, this imposes structure that may not be present in the data such as unimodality and symmetry. The joint PDF nonparametric kernel estimator is given by:

$$f\left(f_j, d_j\right) = \frac{1}{n h_f h_f} \sum_{i=1}^{n} K\left(\frac{f_i - f_j}{h_f}, \frac{d_i - d_j}{d_f}\right) \quad (3)$$

where $K(\cdot)$ is the kernel function, h_f and h_d the bandwidths, and n the number of records. Following Li and Racine [6], likelihood cross-validation was used to select the bandwidths along with the second-order Gaussian kernel. Figure 4 presents the nonparametric kernel estimate of the joint PDF along with the associated probability contour plots, displayed separately in Figure 5.

Figure 4 reveals a unimodal shape of the joint distribution and the presence of one noticeable frequency mode. The contour plot of Figure 4 provides additional information regarding trip concentration. Like in a cartography contour plot, each contour line is a function of time and distance and reports a constant value, in this case the likelihood of a trip being made. Noting that the point of origin corresponds to the parking lot where the car is located, the figure shows that the trips that occurred with the highest frequency are characterized by a distance of about 7-8 miles with a duration between 60 and 70 minutes. The sharp diagonal starting from the origin indicates the strength of the underlying linear relationship between the two variables.

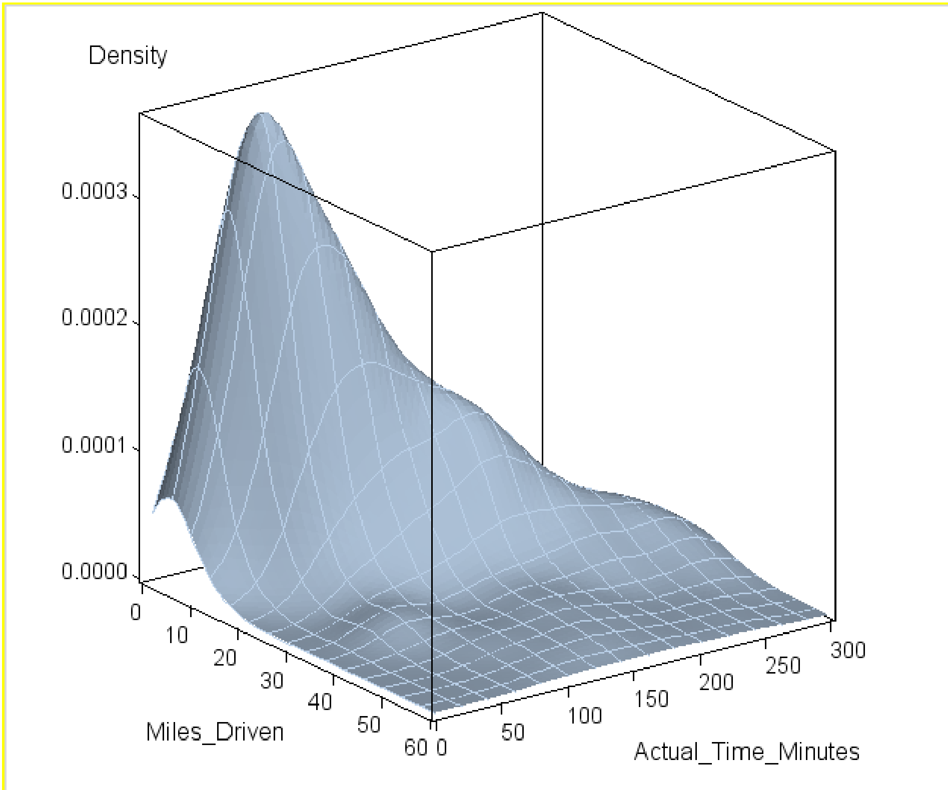

FIGURE 4 Bivariate Density Estimation: Rental Time and Distance

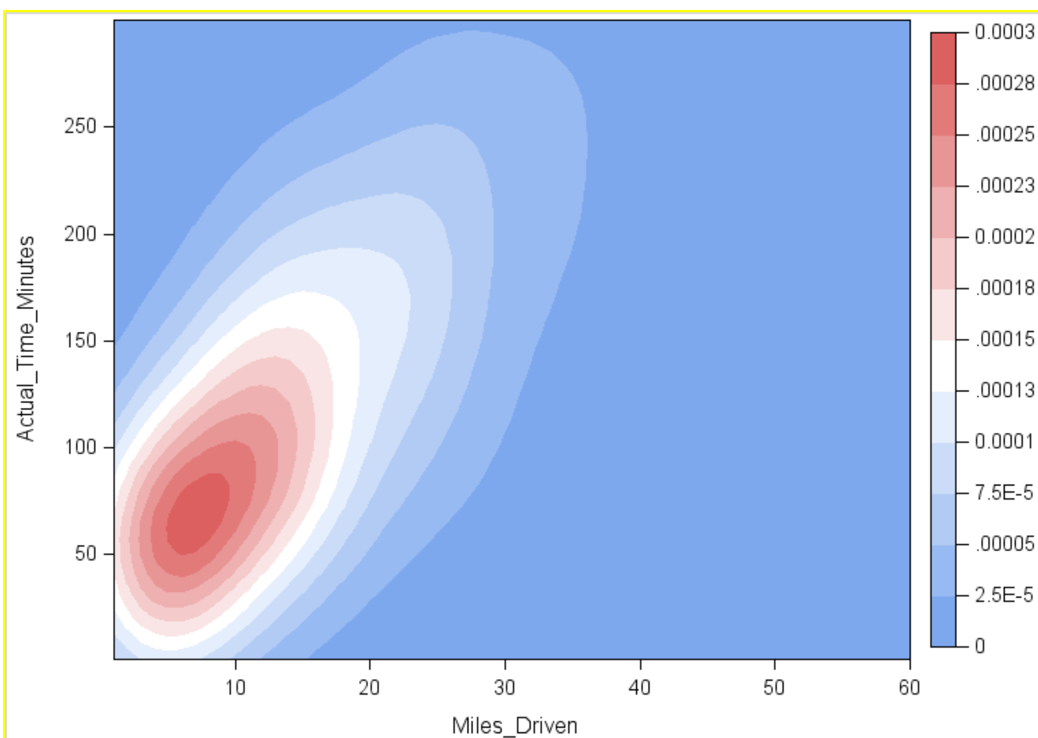

FIGURE 5 Contour Plot of Distance and Time

Applying the bivariate density estimation approach to rental cost and rental duration revealed additional information on carsharing user's trip behavior. FIGURE 6 effectively depicts the behavioral patterns in terms of rental duration and rental cost. Looking at the contour plot of FIGURE 7, it is evident that carsharing users trips were concentrated in two main clusters - the first type having the highest frequency with a relative cost of $8-11 and a duration of 65-70 minutes, and a second type having a much lower frequency with a relative cost of $23-25 and a duration of 170-180 minutes. If TRAC-IT, the GPS-enabled mobile phone application used by the research team to record travel behavior for a sample of users, could have been deployed to all carsharing users (i.e., not just a sample), then it would be possible to geographically pinpoint these two types of trips.

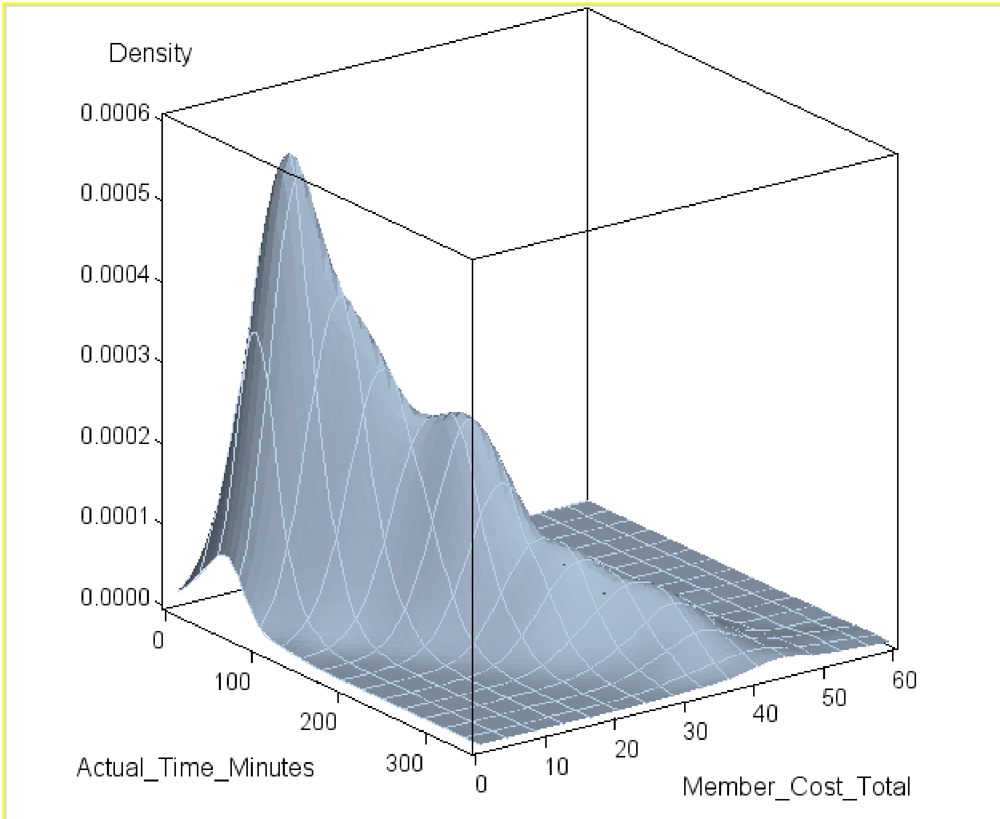

FIGURE 6 Bivariate Density Estimation: Rental Time and Total Cost

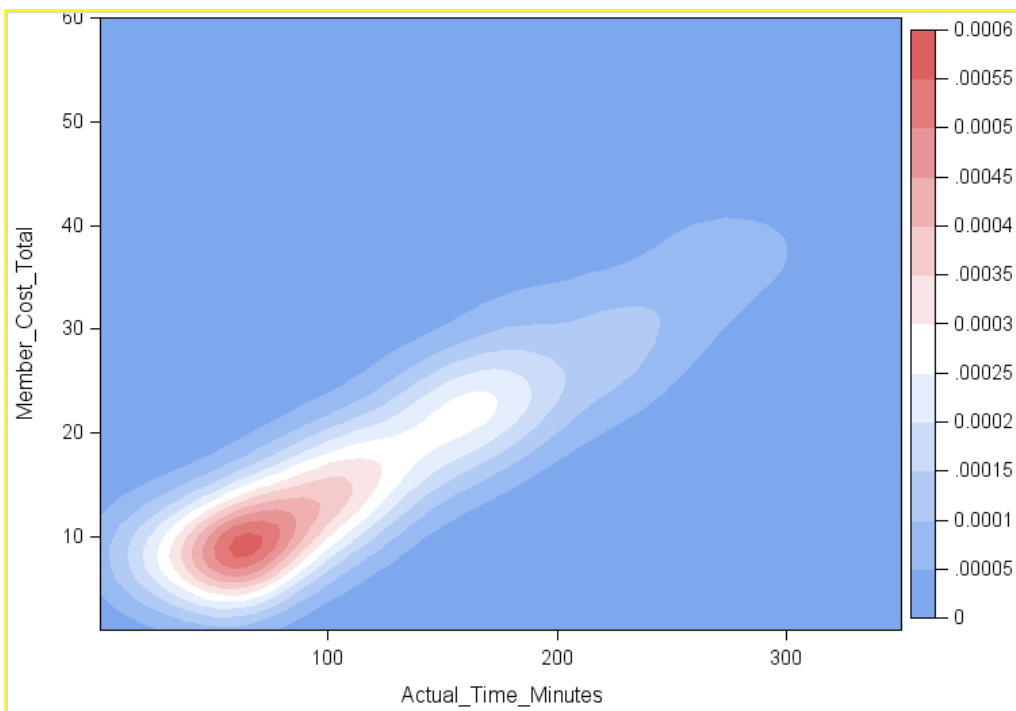

FIGURE 7 Contour Plot of Total Rental Cost and Rental Time

3. INTRODUCING VARIABLE PRICING

At program inception, the rental hourly cost was set to $10/hour for a sedan vehicle (Toyota Prius) and $12/hour for a sport utility vehicle (Ford Escape). Following a review of pricing schedules at the state level, on October 1, 2009, a first change in baseline hourly costs was implemented, while retaining membership fees and overnight and daily charges unchanged, specifically:

- $50 member registration with $30 credit (no change)
- $20 application fee waived (no change)
- $7.50 per hour for Toyota Prius (25% decrease from current $10 per hour; $0.50 below other state universities)
- $9.00 per hour for Ford Escape (25% decrease from current $12 per hour)
- $35 overnight (6 p.m. to 8 a.m. – no change)
- $70 per day (no change)

On November 1, 2010, the researchers implemented a reduction in hourly rates for all users reserving vehicles Monday through Friday, 8:00 a.m. to 6:00 p.m. The price change was set at $6.00 for all vehicles, equivalent to a 20 percent reduction for sedan vehicles and 33 percent reduction of SUVs. This pricing change was implemented to estimate a baseline response to variable pricing, which revealed that carsharing users are highly responsive to price reductions.

The next step was to test the hypothesis that individuals are more likely to rent vehicles at off-peak times contingent upon lower hourly rental costs. Pricing strategies can include lowering (i.e. incentivize) or increasing (i.e., penalize) hourly rates at specific times of the day, based on peak hour definition and congestion (campus or locally based) conditions.

A 50-percent reduction in hourly rates was offered to a randomly selected group of individuals to stimulate demand at off-peak periods, following the schedule shown in Table 1. The pricing strategies were communicated to the treatment group one week in advance of implementation to allow sufficient scheduling time. In addition to the above pricing schedule, a change to the overnight hours was imposed to separate evening peak travel from overnight travel. The new overnight rental schedule was changed from 6:00 p.m. -8:00 a.m. to 8:00 p.m.-8:00 a.m.

TABLE 1 Pricing Strategy

Vehicle	*Rate ($/hour)*	*Time period*
Honda Civic	$3.75	9:00 a.m. to 11:00 a.m. and 1:00 p.m. to 3:00 p.m. --> Monday through Friday (note that the rate goes back to the base rate between 11 a.m. and 1 p.m.)
Nissan Cube	$3.75	9:00 a.m. to 11:00 a.m. and 1:00 p.m. to 3:00 p.m. --> Monday through Friday
Ford Escape	$4.50	9:00 a.m. to 11:00 a.m. and 1:00 p.m. to 3:00 p.m. --> Monday through Friday

3.1 Sample Dataset for Variable Pricing Evaluation

Based on the weekly usage analysis, it was observed that rental frequency varied significantly among carsharing members and that an extended period of data collection would be necessary to observe any response to price changes.

3.2 Collecting Travel Behavior Data

To collect travel behavior data and study participant reactions to variable pricing, the researchers deployed GPS-enabled mobile phones with the TRAC-IT software installed. TRAC-IT is a Java Micro Edition mobile application for GPS-enabled cell phones developed by the National Center for Transit Research [7-14]. TRAC-IT collects GPS data points for all transport modes (e.g., transit, bike, walk, carsharing) every four seconds while the user is moving and provides passive real-time monitoring without requiring real-time interaction with the participant. The research team used TRAC-IT in this study because it provided a high-resolution insight into the geographic and time distributions of participant's travel behavior which was not available from studying the carsharing rental records alone.

To test TRAC-IT, twelve participants were selected for a pilot survey lasting for six weeks during May 2010. Each individual received a gift card at the end of each week.

A first survey of randomly selected individuals (equally split between carsharing and non-carsharing users) was conducted in October-November, 2010, with 21 participants surveyed for a six-week period. A second survey was conducted in February-May 2011, with 30 participants tracked for a nine-week period. At the beginning of the survey period, each participant was given a low-cost GPS-enabled flip phone with the TRAC-IT software pre-installed. The TRAC-IT server sent daily email reminders to participants with a link to the previous day's trips displayed in Google Earth and asked the participant to provide a brief description of purposes and modes of transportation for their trips. Participants were asked to charge cell phones nightly and were given a wall charger and a second charger that doubles as a wall charger and car charger. A car charger was also left in the glove box of the carsharing rental cars.

TRAC-IT collected 1,857 sessions from 30 users (over 60 sessions on average per user) for 4,023,917 GPS data points from February 10 to April 29, 2011 when variable pricing strategies were tested. TRAC-IT collected an average of 40 days' worth of travel behavior data collected per participant, with approximately 1,195 total survey person days. Lost trips during this period due to technology failures were minimal, as the TRAC-IT Web Application server up-time during this period was over 99 percent.

The final dataset consisted of a subset of the entire TRAC-IT database, comprising 1,633 trips made by 30 sampled users. For this study, the GPS data were manually segmented into discrete trips by data analysts and labeled with the purposes and modes of transportation according to the participant feedback emails. This data was also used to evaluate a novel point-of-interest (POI) detection algorithm which attempts to automatically identify POIs where the user spent significant amount of time as well as the trips that are defined by the travel behavior from one POI to another. Ultimately, the research team decided to use the manually-segmented trip data for analysis since the POI detection algorithm required further improvements at the time of the study [5].

An analysis of the final dataset showed that most of the trips are made by car, followed by walking, bike, bus, and carsharing (Table 1). The vast majority of the trips were related to students-specific activities, like going to school, returning home, or going to work. Respondents did not report 16% of their trip purposes.

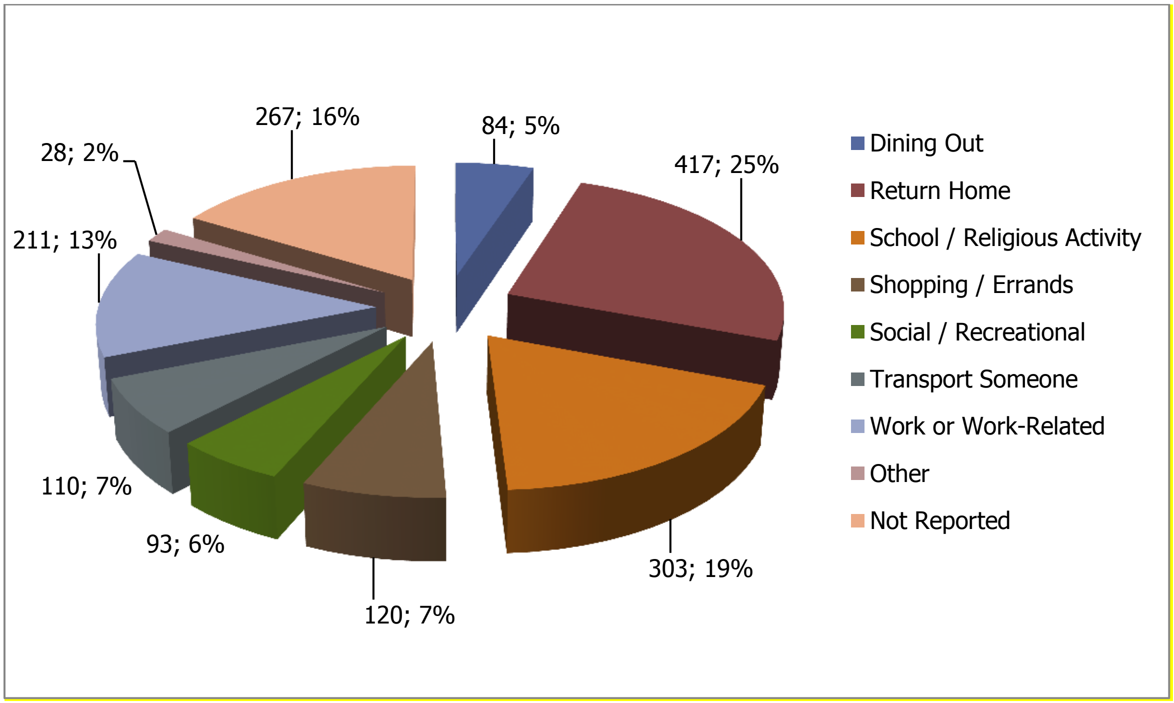

FIGURE 8 Trip Purpose - TRAC-IT User Sample

3.3 Impact on Time-of-Day Use

To test the hypothesis that trips are distributed differently by time of the day, changes in the univariate temporal structure of trips subject to dynamic pricing were explored. This was achieved by employing nonparametric density estimation methods to estimate probability density functions (*PDF*) of car rentals by time of day. Nonparametric methods are becoming commonplace in applied settings, and have been successfully used to enhance understanding of empirical phenomena [15-17]. Beyond the proper selection of the kernel functions stands the most relevant choice of the smoothing parameter. There exists no general formula to select the optimal smoothing parameter. The heuristic plug-in method is generally used given its ease of implementation on readily available commercial software packages, although limited to the univariate and bivariate cases. Li and Racine [6], discuss the use data driven methods, such as maximum likelihood or least square cross-validation, to select optimal bandwidth parameters of conditional PDF, showing relevant benefits in terms of optimal smoothing and relevant predictors' selection. This study follows- this approach to univariate and joint multivariate PDF estimation.

FIGURE 9 shows the temporal distribution of trips with and without the pricing strategy. The wider distribution of trips with no pricing intervention shows that rentals were widely distributed throughout the day to include the p.m. peak period. The PDF provides evidence of the impact of dynamic pricing on peak-hour travel. The PDF without dynamic pricing intervention has a unimodal shape with peak period usage at noontime, whereas the PDF, following the implementation of the 9-11 a.m. and 1-3 p.m. pricing schedule, has a radically different shape. The latter shows how pricing shifted the time a carsharing vehicle was reserved and used in the 9-11 a.m. and in the 1-3 p.m. windows.

The figure also shows an increase in trips that occurred after the p.m. off-peak discount (around 5-6 p.m.) coinciding with the beginning of evening rental discounts offered as part of the carsharing program. This analysis provides evidence that longer evening trips may have happened when individuals enjoyed the discount in the p.m. hours and decided to extend vehicle usage beyond the discount window (i.e., flowing into the evening). This most likely did not happen in the a.m. period when individuals faced more binding constraints (e.g., get back to work or school).

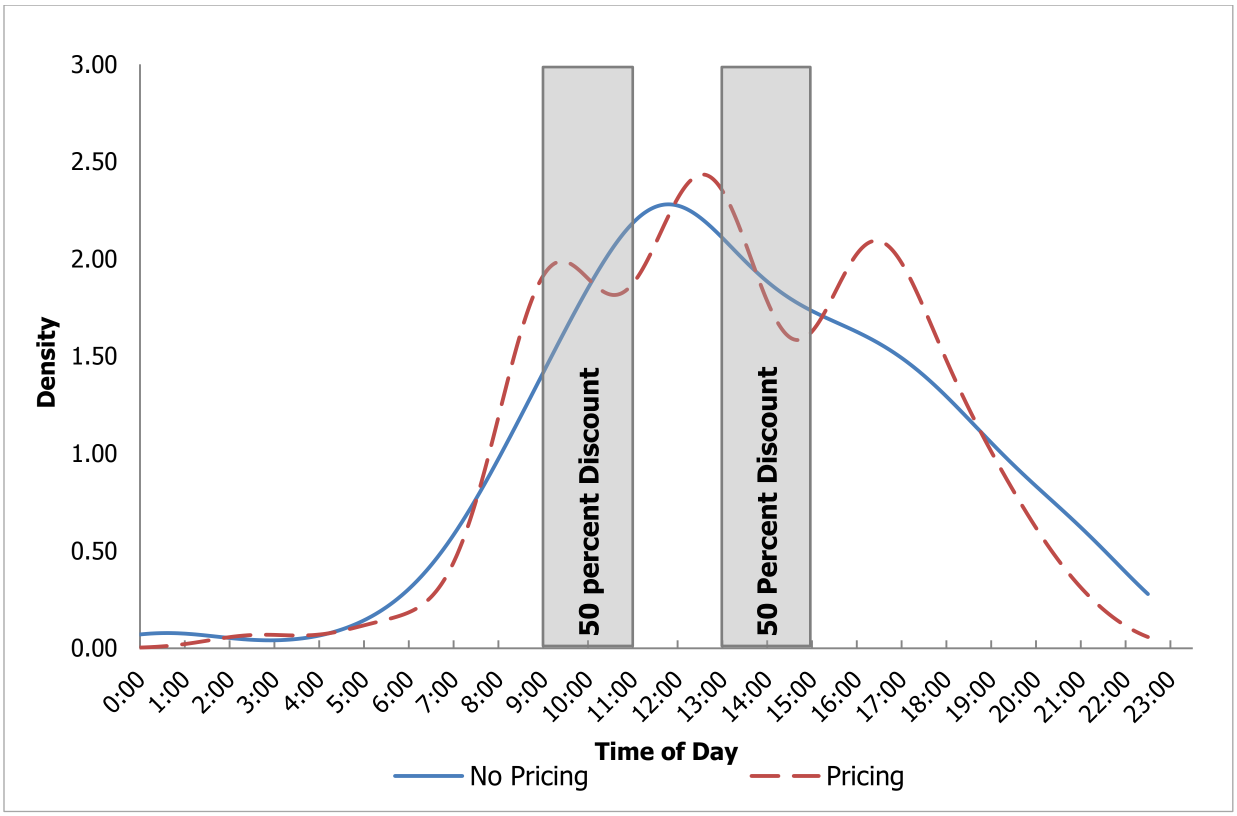

FIGURE 9 Univariate Density Distribution of Carsharing Trips by Time of Day

3.4 Impact on Activity-Travel Patterns

Table 2 reports average trip lengths, number of trips, and SDE size by day of week. The table shows that although the average number of trips did not vary, the spatial dispersion of out-of-home activities was greater over the weekend, with an average SDE size of 23.1 square miles over its mean center. This is consistent with the tendency to undertake leisure or discretionary trips during the weekend, usually characterized by longer distance trips.

TABLE 2 Average Trip Length, Number of Trips and SDE

Day	*Trips*	*Distance (miles)*	*SDE (square miles)*
Sunday	4.30	6.30	23.10
Monday	4.90	3.60	18.60
Tuesday	4.70	2.50	2.70
Wednesday	5.40	2.50	4.00
Thursday	4.30	4.60	2.90
Friday	4.70	4.40	3.40
Saturday	3.10	12.20	7.10
Average	4.70	4.00	6.90

Table 3 compares the size of the activity space for carsharing and non-carsharing users, by reporting a comparison of means of trips and SDE size. While individuals identified as carsharing users engaged in shorter trips (2.6 miles) than all other users (4.2 miles), they relied on carsharing to make longer trips (8.0 miles vs. 1.7 miles for non-carsharing trips).

TABLE 3 Mean Comparison of Trip Length and SDE, Carsharing vs. Non-Carsharing

	Trip Length (miles)			*SDE (square miles)*		
User Type	Average	*Carsharing Trip*	*Non-Carsharing Trip*	Average	*Carsharing Trip*	*Non-Carsharing Trip*
Carsharing	2.6	8.0	1.7	0.5	0.2	0.5
Non-Carsharing	4.2	-	4.2	7.8	-	7.8

Results of mean comparison tests confirmed that carsharing users had a much smaller activity space (0.5 square miles) than all other sample individuals (7.8 miles). This might be because carsharing users do not have access to a private vehicle and therefore only rely on carsharing to conduct out-of-home trips for routine and recurring “maintenance activities,” such as shopping or other errands. Table 3 also shows that carsharing user activity space contracted while using carsharing as a mode of transport. This result is somewhat counterintuitive as one might think that by relying on carsharing, individuals would be able to reach locations that are not available by other means of transport. Reduced activity space for carsharing is confirmed by measuring the size of the activity space by using the SDD instead of the SDE. The SDD is more sensitive to the presence of outliers, or trips that are longer than usual, while the SDE reduces the outlier effect, while accounting for spatial-directional bias (trips made to the same location with more frequency). The fact that the size of the SDE is smaller when carsharing users relied on carsharing indicates that they tended to make the same trip type to the same location when using this mode, thus determining a SDE with an elongated ellipse. This is consistent with the assumption that carsharing among university members is used to conduct maintenance trips (higher frequency, constant locations).

An examination of the joint bivariate distribution (Figure 10) of trips by cost and rental time after off-peak pricing discounts were introduced shows that trips tend to be longer in duration during less expensive travel times. The underlying contour plot of Figure 11 confirms this findings by showing a some trips lasting more than five hours, corresponding to trip taking during the evening rental discounts, which were offered as part of the carsharing program. The analysis provides evidence that longer evening trips might happen when individuals enjoying the 1 p.m. to 3 p.m. discount decide to extend vehicle usage beyond the discount window (flowing into the evening). This most likely does not happen in the morning period when individuals face more binding constraints (i.e., get back to work or school).

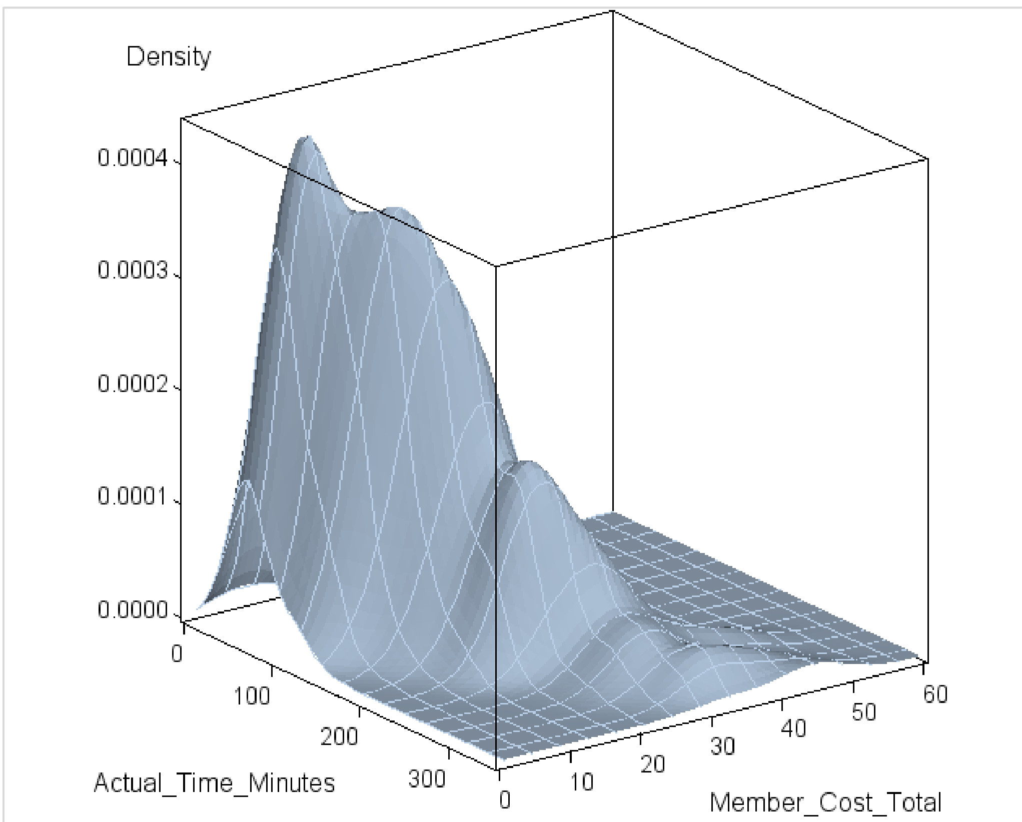

FIGURE 10 Contour Plot of Total Rental Cost and Rental Time: Dynamic Pricing

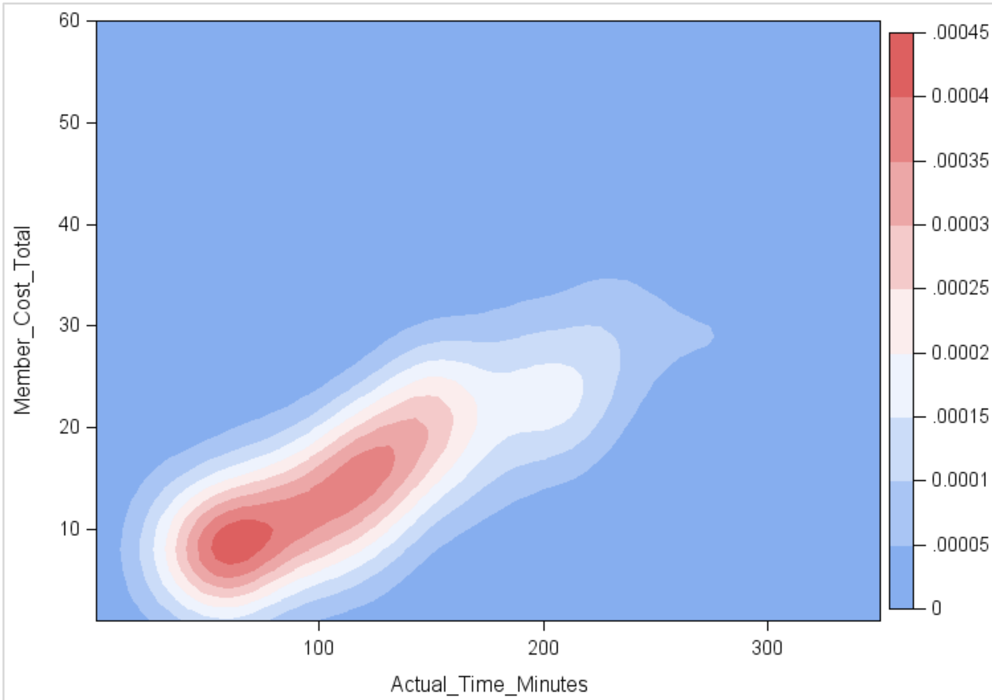

Figure 11 Bivariate Density Estimation of Rental Time and Cost: Dynamic Pricing

4. CONCLUSIONS

Previous research has found that carsharing customers increase their use of carpooling, bicycling and walking. While modal shift is one outcome likely to reduce traffic congestion, carsharing can provide increased accessibility to those who do not own a vehicle and potentially add more vehicles to the system. As carsharing programs grow, the ability to influence when these carsharing trips occur can have a bearing on localized congestion. This study examined how variable pricing can be applied to the carsharing model to influence when a carsharing trip is taken. Specifically, this project tested an innovative approach to pricing carsharing by introducing pricing based on time-of-the-day and day-of-the week. The program was tested in a car-centric university setting, with limited transit options. To collect travel behavior data, GPS-enabled mobile phones with tracking software TRAC-IT were used to follow a sample of participants and provide longitudinal information on the program's impacts, including the temporal and spatial dispersion of daily trips.

The empirical analysis shows that overall carsharing program users are price sensitive, and changes in rental rates in the order of 20 to 50 percent have a significant impact on daily rental times. Following the implementation of a pricing schedule to incentivize users to rent vehicles at off peak times, there is evidence that variable pricing can modify peak-hour carsharing travel. Changing the pricing schedule to reduce the hourly rental rates in the periods immediately before and after the peak influenced when carsharing trip generation. The probability density function without dynamic pricing intervention has a unimodal shape with peak period usage at noontime, whereas the PDF, following the implementation of the 9 a.m. to 11 a.m. and 1 p.m. to 3 p.m. pricing schedule, has a radically different, bimodal, shape. The results of this analysis indicate that reducing rental rates to incentivize use in off-peak periods might produce positive results.

The use of variable pricing demonstrated that carsharing users respond to financial incentives by shifting trips outside of the regional peak-period travel or by delaying the start of the evening rental. In this study, pricing strategies were designed to shift travel from local congested peak-hour travel. Pricing took the form of discounts of baseline hourly rates during off-peak travel times.

Future research is needed to test if the response would be the same by penalizing carsharing travel during peak-hour travel (i.e., increasing hourly rates). Further research is also needed to investigate the effect of dynamic pricing on scheduling behavior. To use carsharing, individuals make reservations based on their planned travel schedule by checking for vehicle fleet availability. The process is comparable to air travel booking, requiring activity-travel and trip planning. This process is easier for individuals with fixed schedules and/or less time constraints. For example, employees following a regular working schedule or students with a predetermined class calendar might be able to plan with more certainty the use of carsharing vehicles over the course of a week or an entire month, as opposed to more casual users. By dynamically managing vehicle scheduling, further research could investigate the impact on activity-travel scheduling and trip-making behavior and test its effect on peak-hour travel shifts. Changing rental costs based on scheduling patterns might also provide additional insight into carsharing impacts on long-term changes in travel behavior.

AKNOWLEDGEMENTS

The authors wish to thank Allen Greenberg, Senior Policy Analyst at U.S. Department of Transportation Federal Highway Administration, Congestion Management and Pricing Team, for his support and insight throughout the study.

REFERENCES

1. Martin, E., S. Shaheen, and J. Lidicker, *Impact of Carsharing on Household Vehicle Holdings: Results from North American Shared-Use Vehicle Survey.* Transportation Research Record: Journal of the Transportation Research Board, 2010(2143): p. 150-158.
2. Millard-Ball, A., et al., *Car-Sharing: Where and How it Succeeds*, 2005, Transit Cooperative Research Program: Washington, D.C.
3. Martin, E. and S. Shaheen, *The Impact of Carsharing on Public Transit and Non-Motorized Travel: An Exploration of North American Carsharing Survey Data.* Energies, 2011(4): p. 2094-2114.
4. Shaheen, S.A., A.P. Cohen, and M.S. Chung, *North American Carsharing: 10-Year Retrospective.* Transportation Research Record: Journal of the Transportation Research Board, 2009. **2110**: p. 35-44.
5. Winters, P.L., et al., *Value Pricing Pilot Program-Variably Priced Carsharing Project*, 2012, Office of Transportation Management, HOTM, Federal Highway Administration, U.S. Department of Transportation: Washington, D.C.
6. Li, Q. and J.S. Racine, *Nonparametric Econometrics: Theory and Practice*2007: Princeton University Press.
7. *TRAC-IT*. Location Aware Laboratory 2012; Available from: http://www.locationaware.usf.edu/ongoing-research/projects/trac-it/.
8. Barbeau, S., N.L. Georggi, and P.L. Winters, *Dynamic Travel Information Personalized and Delivered to Your Cell Phone* 2011, National Center for Transit Research.
9. Barbeau, S.J., et al., *TRAC-IT: Software Architecture Supporting Simultaneous Travel Behavior Data Collection and Real-Time Location-Based Services for GPS-Enabled Mobile Phones*, in *Transportation Research Board 88th Annual Meeting*2009: Washington, D.C.
10. Barbeau, S.J., et al. *Dynamic Management of Real-Time Location Data on GPSEnabled Mobile Phones*. in *UBICOM 2008 International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*. 2008.
11. Barbeau, S.J., et al., *System and Method for Determining Critical Points in Location Data Generated by Location-Based Applications*, in *U.S. Patent and Trademark Office*2008.
12. Barbeau, S.J., et al., *Optimizing Performance of Location-Aware Applications Using State Machines*, in *U.S. Patent and Trademark Office*2011.
13. Barbeau, S.J., et al., *Architecture and Two-Layered Protocol for Real- Time Location-Aware Applications*, in *U.S. Patent and Trademark Office*2011.
14. Barbeau, S.J., et al., *Adaptive Location Data Buffering for Location-Aware Applications," Patent* in *U.S. Patent and Trademark Office*2011.
15. Kharoufeh, J.P. and K.G. Goulias, *Nonparametric Identification of daily activity durations using kernel density estimators.* Transportation Research Part B, 2002. **36**: p. 59-82.
16. Pagan, A. and A. Ullah, *Nonparametric Density Estimation*1986: Cambridge University Press.
17. Scott, D.W., *Multivariate Density Estimation: Theory, Practice, and Visualization*. Wiley Series in Probability and Statistics1992: Wiley.