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First Year Evaluation for San Diego Gas & Electric's Electric Vehicle Pilot

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1 Executive Summary

This report documents results from the first year of San Diego Gas & Electric Company's (SDG&E's) multi-year electric vehicle (EV) Rate Experiment. These results are preliminary and this progress report may not reflect results in the future final report. A final report on this experiment is expected after 2013 results are analyzed.

This experiment uses an innovative research design based on a randomized pricing experiment to provide an early view of EV owner response to time-varying rates for EV charging. In this experiment, a group of SDG&E customers with EVs have been randomly assigned to one of three experimental time-of-use (TOU) rates specifically for their EV charging. The timing of EV charging has major implications for a utility's ability to preserve reliability of the distribution system as EV penetration increases in its service territory. If EVs are charged at peak times, then each one added to a neighborhood is about the equivalent of an additional household worth of load added to that neighborhood.[1] This could require distribution upgrades, as well as additional stress on distribution equipment. On the other hand, if EV owners can be induced to charge during off-peak times, then the stress and risk on the distribution system will be much less.

The bottom line finding from the first year of this study is that TOU pricing rates in conjunction with a charging timer lead to the vast majority of EV owners charging overnight rather than during peak times. Customers in the study use an average 8.3 kWh of home charging energy per day and roughly 80% of that has taken place during the super-off peak period of the study's time-varying rates. This value does not vary much across the rate groups within the experiment, with the lowest value of 78% occurring for the customers subject to the mildest time-varying rate. The charging timer appears to make it so easy to charge overnight that even a quite mild rate differential induces a strong tendency for overnight charging. Greater detail about this and related findings are provided in this report, but this conclusion is promising to utilities faced with managing increased EV ownership. Over the course of the second year of the study, it will be important to determine whether this pattern persists.

This report also includes an analysis of the relationship between customer charging patterns and self-reported data from the same customers on a survey completed in the winter of 2011-2012. The primary survey results were reported in an earlier project report.[2] However, the analysis reported here is the first to link responses to observed load data. Two major findings emerge from this analysis: first, self-reported charging behavior is indicative of actual charging behavior; and second, there are no strong relationships between charging behavior and income, education or age.

Finally, this report includes an economic demand model of charging behavior, fitted to the observed charging data.[3] In order to apply findings from this study to other charging prices that might be

[1] Typical peak EV charging load for a given household in this study is 2-2.5 kW. Households in SDG&E's territory typically have peak summer time loads of 1-2 kW. This value varies depending on many factors, such as the presence of central air-conditioning.

[2] See "Interim Report for San Diego Gas & Electric's Electric Vehicle Pilot," prepared by Freeman, Sullivan & Co. for SDG&E.

[3] The analyses in this report focus on the charging behavior of customers who opted to be a part of the pricing experiment by being assigned to one of three experimental charging rates. There is also a group of customers who have chosen not to be on one of those rates, but who are still part of the broader study and whose whole-house load data is of interest for this study. An analysis of those customers' charging behavior was documented in the interim report mentioned above and

considered for the future or for other jurisdictions, we estimated a model of the economic trade-offs that a customer faces when choosing to charge at one time as opposed to another. The model used here, known as a generalized Leontief model, is a standard way of accounting for these trade-offs. The main conclusion from this model is that customers appear to be more responsive to on-peak prices when price ratios are higher. The model is also used to predict usage levels under alternative price schedules not included in the experiment; those results are shown in the body of the report.

another such analysis will be included in the second year report on this project. This report does not contain any analysis of charging behavior of customers not on one of the three experimental TOU rates.

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2 Introduction

In April 2010, SDG&E began recruiting customers for a multi-year EV rate experiment taking place from early 2011 to mid 2013. This experiment is designed to investigate several areas of customer behavior related to EV usage and charging. San Diego is 1 of 18 major cities selected by the EV Project as a test site for evaluating plug-in electric vehicles (PEVs).[4] Nissan plans to sell 1,000 LEAF PEVs[5] in San Diego. These vehicles are battery electric vehicles, not plug-in hybrid electric vehicles.

As part of the EV Project, all customers purchasing a LEAF were offered no-cost electric vehicle supply equipment (EVSE) for home installation (approximate value $1,499), up to $1,200 credit towards the installation of the equipment and a DC Fast Charge port on the car at no charge (approximate value $700).[6] The EVSE is then installed at the EV owner's home and provides power at 240 Volts at 30 Amps as compared to 120 V at 12 A from an EV Cord Set in a standard wall outlet; higher voltage allows for faster vehicle charging than can be accomplished through a standard wall outlet. Charging the LEAF at 120 V adds approximately 5 miles of range per hour of charging, while 240 V charging adds approximately 12 miles of range per hour of charging (depending on driving style and driving speed). A full charge of the LEAF takes up to 20 hours from an EV Cord Set and up to 7 hours from the EVSE, depending on the EV's state of charge at the beginning of the charging session. The EVSE, installed on a dedicated branch circuit of the home's electric distribution system, also allows for a separate meter to be installed for measuring the electric consumption due to EV charging.

The installation cost for EVSE ranges from about $600 to several thousand dollars, depending on the configuration of the customer's home and on the electrical complexity of the installation. In many cases, the $1,200 credit offered by ECOtality for installation covers the entire cost of the installation. The customer is obligated to pay for any installation costs above $1,200.

The goals of the SDG&E's rate experiment are to understand the potential impact of EV technology on the electric utility infrastructure and identify methods to mitigate grid impacts. The FSC Group (FSC), in this report, provides estimates of the impact of EV technology and three different EV-specific TOU rates on the energy consumption of pattern of participating customers approximately one year after most customers received their vehicle and charger. FSC's analysis uses electricity usage data for the EVSE (obtained from a dedicated utility billing meter), surveys of participant customers and demographic information to answer a number of important questions, including:

- What are the impacts of the various TOU rates on charging behavior?
- How is charging behavior affected by the availability of EVSE timers?
- Do charging patterns change over time as customers become more familiar with the technology?
- How does charging behavior vary across different demographic segments?

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[4] The EV Project is funded by DOE and the California Energy Commission, and managed by ECOtality. See www.theevproject.com for more details.

[5] All vehicles in the SDG&E rate experiment are PEVs (all electric Plug-in Electric Vehicles); however, for simplicity we refer to these vehicles as EVs in this report.

[6] This equipment and installation subsidy is provided by ECOtality and funded partially by DOE and partially by shareholders of ECOtality.

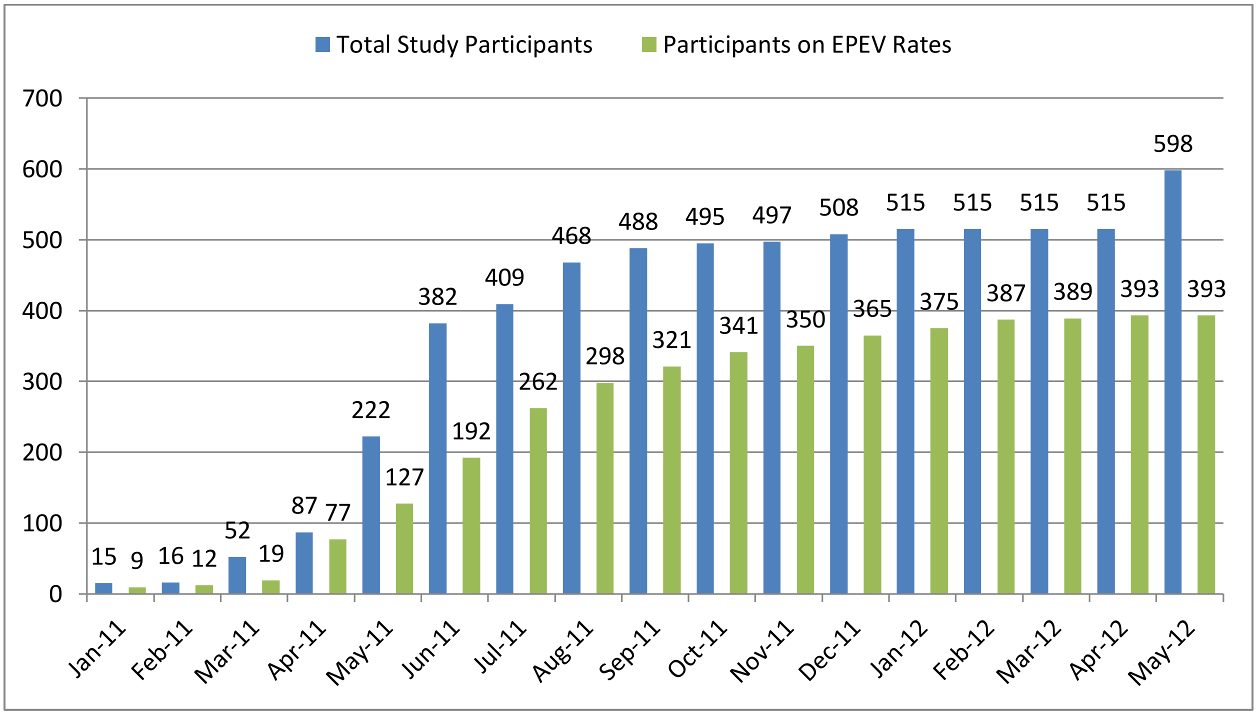
The rate experiment tested three TOU rates, each of which has three periods: peak, off-peak and super off-peak. Customers who chose to be part of the rate experiment are randomly assigned to one of the three TOU rates for the duration of the study. The rates apply only to load from the EVSE and not to the customer's entire house load. There are different prices for charging at different time periods during the day (referred to as "on-peak," "off-peak" and "super off-peak"). The on-peak period runs from noon to 8 PM, the off-peak period runs from 8 PM to midnight and 5 AM to noon, and the super off-peak period runs from midnight to 5 AM. These TOU periods do not vary by day of week and make no exceptions for holidays. The three rates are designed to test low, medium and high price ratios, between the super off-peak to on-peak prices. In addition, there are different price ratios between the three rates in the on-peak to off-peak price and between summer and winter seasons.

The EVSE and EV come with a timers that allows customers to set the time of day at which charging will begin. This technology may have a strong impact on the charging behavior of EVSE users, by making it easier for them to charge during a preferred time.

As of May 2012, 598 EVs in the SDG&E service territory were participating in the pilot, and 393 of them had been assigned to 1 of the 3 experimental EV rates. Figure 2-1 presents EV study enrollment over time, including both customers on experimental rates and all customers in the study, and Figure 2-2 presents active participants by location.[7] The number of enrollments showed an initial acceleration, followed by a leveling off in late 2011. Study participants are spread throughout the service territory, with the highest number in Carmel Valley (ZIP code 92130).

[7] Not included in the charts are 48 participants who dropped out of the study; there are no start or stop dates associated with these participants.

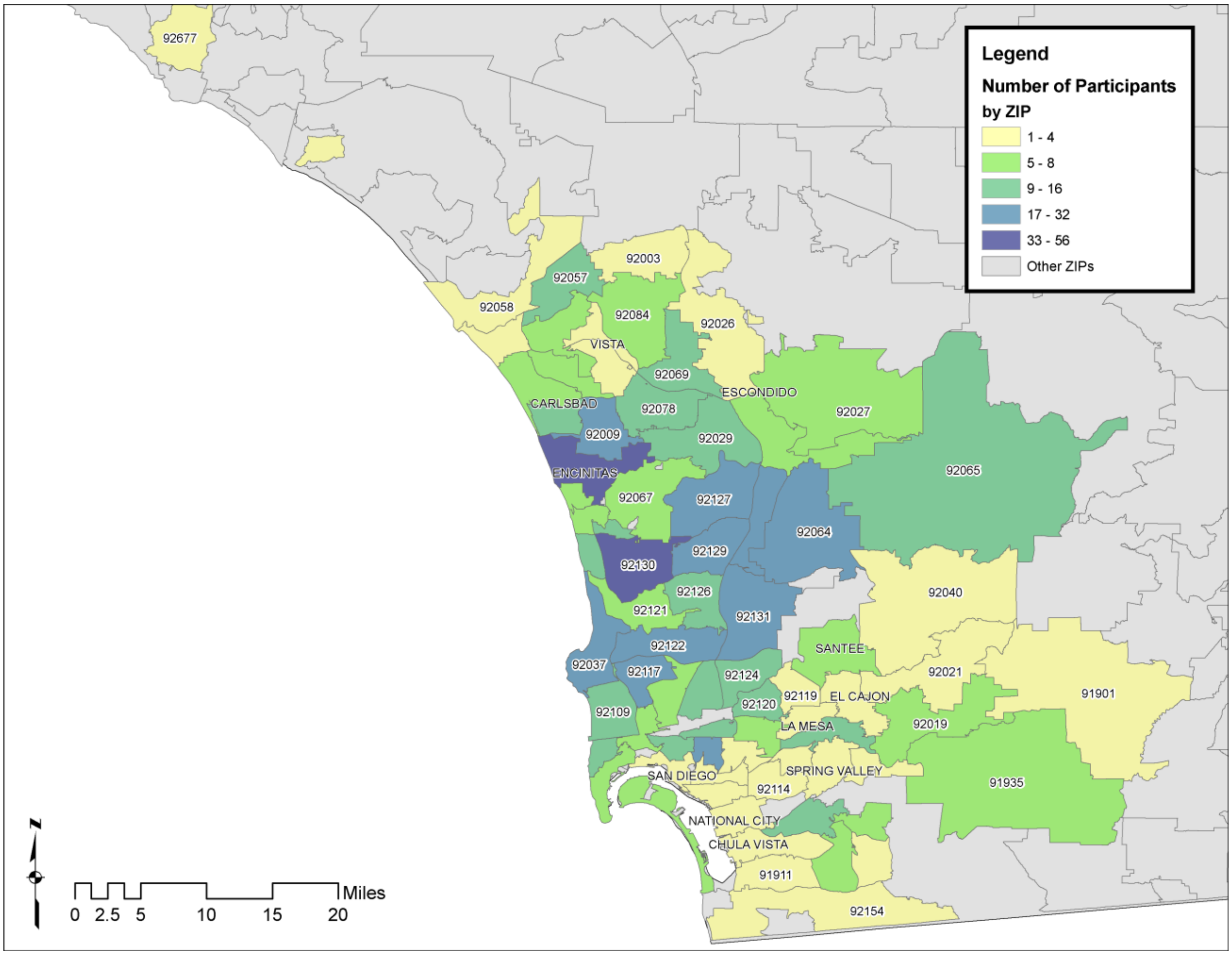
Figure 2-1: Cumulative Number of Study Participants[8,9]



8 These numbers are obtained from estimated EV delivery dates. Specific delivery dates for those received after January 2012 are not available.

9 Note that there is a gap in enrollment date information, which leads to the flat enrollment in the study from January to May 2012.

Figure 2-2: Active Study Participants by ZIP Code



Those customers who accept the EVSE offer from the EV Project, and whose residences are compatible with EVSE installation, are also offered the opportunity to take part in the SDG&E rate experiment. In this experiment, customers with an EVSE may elect to be randomly assigned to one of three experimental TOU rates for EV charging use. The experimental rates require a dedicated meter used for billing that captures the EVSE load. The second meter installation is typically performed during the same time as the EVSE installation. SDG&E paid the cost of the equipment necessary for the second meter, which includes the dedicated meter, a meter socket box and an electrical disconnect switch.

There are two options for customers who take part in the EV Project, but who do not elect to be assigned an experimental rate. First, SDG&E currently offers an electric vehicle TOU rate (Schedule EV-TOU-2) that applies to the entire load of a customer’s home (whole house). This rate schedule also has three rate periods but has an on-peak period that runs from noon to 6 PM rather than noon to 8 PM. The rate’s TOU period definitions also do not vary by day of week. However, the EV-TOU-2 on-peak period moves to off-peak status on holidays. Second, customers may continue to have all their usage, including EV charging, billed on their current rate, which for most participants is the standard residential rate, Schedule DR.[10] Schedule DR is an usage based increasing block rate, undifferentiated over time. EV Project customers are not required to participate in the rate experiment in order to receive an EVSE as part of the EV Project.

2.1 Participant Characteristics

Table 2-1 lists details of the experimental rate schedules of participants in the rate experiment. Participants who opted in to the rate experiment were randomly assigned to an EV charger-specific experimental rate schedule (EPEV-L, EPEV-M or EPEV-H). The rates are named EPEV-X, EPEV-Y and EPEV-Z in the SDG&E tariff book. We use the suffixes L, M and H to make it clear which rates have stronger price ratios or signals. The low price ratio is designated L, while the high price ratio is designated H; M designates a price ratio in between the L and H rates. Table 2-1 includes the non-experimental whole house EV-TOU-2 rate for comparison purposes.

Early in the experiment, participants were randomly assigned to one of two rate schedules (EPEV-H or EPEV-M); after a few months, a third rate schedule (EPEV-L) was added to the recruitment scheme. EPEV-L has price ratios similar to the EV-TOU-2 rate. Use of the third rate schedule allows for a better understanding of customers' demand for charging load at different times of the day. Also, independent sources of variation in two of the three TOU periods will allow for a fully-identified demand model of charging behavior.

Table 2-1: Rate Schedules of Study Participants[11]
Total Rates Effective July 1, 2012

Period		EV-TOU-2		EPEV-L		EPEV-M		EPEV-H	
		$/kWh	Ratio to Super Off-peak	$/kWh	Ratio to Super Off-peak	$/kWh	Ratio to Super Off-peak	$/kWh	Ratio to Super Off-peak
Summer	Peak	$0.24	186%	$0.25	202%	$0.27	383%	$0.36	571%
	Off-peak	$0.15	117%	$0.16	123%	$0.17	241%	$0.14	228%
	Super Off-peak	$0.13		$0.13		$0.07		$0.06	
Winter	Peak	$0.16	122%	$0.17	124%	$0.23	303%	$0.32	483%
	Off-peak	$0.15	117%	$0.16	119%	$0.15	202%	$0.13	193%
	Super Off-peak	$0.13		$0.13		$0.08		$0.07	

The three experimental rate schedules differ by the ratio of on-peak to super off-peak rates. EPEV-L has the lowest ratio, offering participants fairly mild incentives to charge during the super off-peak period. During the summer, the on-peak rate ($0.25/kWh) is just under two times the super off-peak

[10] See Figure 2-1 for details on the fraction of customers choosing EPEV rates versus other rate options.

[11] These Rate Schedules represent the total bundled rates include the Utility Distribution Company (UDC) total, and the Department of Water Resources Bond Charge (DWR-BC) and Electric Energy Commodity Charge (EECC) rates. The experimental rates are actually named EPEV-X, EPEV-Y and EPEV-Z in the SDG&E tariff book. We use the suffixes L, M, and H to make it clear which rates have stronger price signals. Prices are rounded to two decimal places to simplify presentation in Table 2-1.

rate ($0.13/kWh). During the winter, the on-peak rate ($0.17/kWh) is 24% higher than the super-off-peak rate ($0.13/kWh).

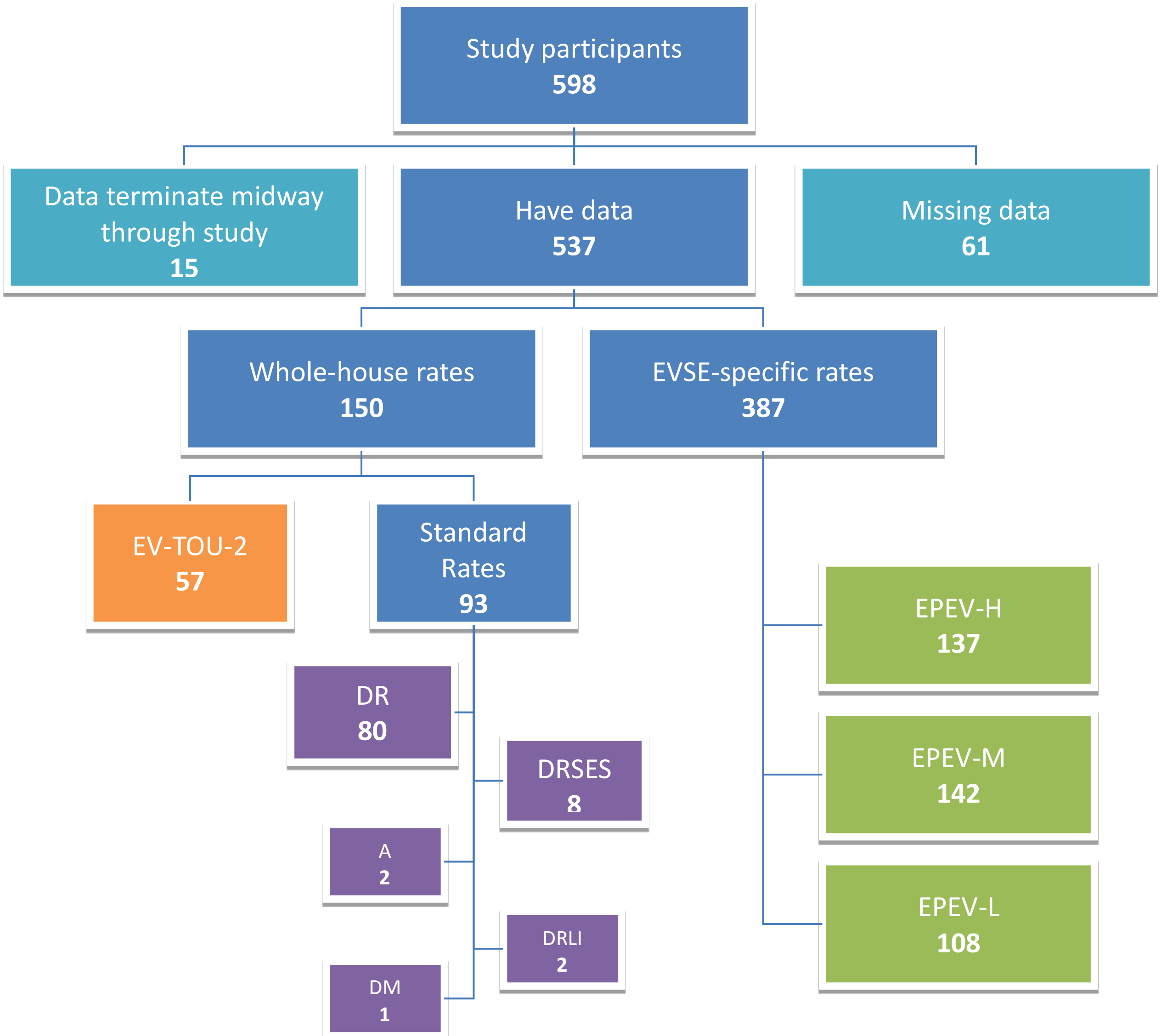
EPEV-M has a larger price ratio. During the summer, the on-peak rate ($0.27/kWh) is just under four times the super off-peak rate ($0.07). During the winter, the on-peak rate ($0.23/kWh) is almost three times the super off-peak rate ($0.08/kWh).

EPEV-H has the largest price ratio and is intended to provide the largest incentive for super off-peak charging. During the summer, the on-peak rate ($0.36/kWh) is six times the super off-peak rate ($0.06/kWh). During the winter the on-peak rate ($0.32/kWh) is nearly five times the super off-peak rate ($0.07/kWh).

The three rates also differ in their ratios of on-peak to off-peak prices, as shown in Table 2-1. Here again, EPEV-L provides the mildest price differentials and EPEV-H provides the strongest on-peak to super off-peak ratio. In general, the price ratios are lowest for EPEV-L, and increase for EPEV-M and EPEV-H.

Figure 2-3 presents the number of study participants for whom interval data is available as of May 30, 2012, by rate schedule. Of participants for whom interval data is available, 150 do not have a separate EVSE rate schedule. Of these customers, 57 have opted for the EV-TOU-2 rate and 93 currently remain on standard (i.e., non-EV) rates. Most customers on standard rates elect the DR rate schedule.

Figure 2-3: Number of Customers with Interval Data, by Rate Schedule
As of May 30, 2012



Another important customer characteristic is the presence of a solar photovoltaic (PV) system. PV systems are present in 204 (38%) of participant households who have interval data, as shown in Table 2-2. This is an important issue because these customers face quite different incentives regarding their charging behavior. Specifically, they may be more apt to charge their vehicles during the day using the energy from their PV system, which they would otherwise get a credit for providing to the grid. Table 2-2 shows the distribution of customers over rates and whether or not they have PV. Virtually all customers who opt-out of the EV rates have PV systems (94%), but the converse is not true; there is a substantial group of customers who have PV systems and are on an EV rate. The fact that almost all EV customers on non-TOU standard rates have PV systems suggests that EV customers with PV systems make systematically different decisions about rates, most likely to maximize economic benefits from their PV systems. Additionally, in this population, behavior of customers not on EV rates is driven almost completely by customers with PV.

Table 2-2: Customers with Household PV, by Rate

Rate Schedule		Have PV system	No PV system	% have PV system
EV Rate	EPEV-H	35	102	26
	EPEV-M	36	106	25
	EPEV-L	27	81	25
	EV-TOU-2	22	35	39
Total on an EV Rate		120	324	27
Standard Rate (no EV rate)	DR	76	4	95
	DR-LI	2	0	100
	DR-SES	8	0	100
	DM	1	0	100
	A	0	2	0
Total not on an EV Rate		87	6	94
Total on PV		207	330	39

It is reasonable to assume that this population of PEV drivers and owners is probably similar to near-future PEV drivers and owners. This study does not attempt to generalize its findings beyond this population of PEV consumers.

The remainder of this report is organized into four sections and two appendices. Section 3 presents several analyses of interval load data associated with EV chargers and premises of the study participants. Section 4 discusses the results of a survey of pilot participants that was performed in December 2011 in light of the charging behavior observed for the same participants. Section 5 presents the findings of the econometric analysis of an EV charger demand model. Section 6 concludes with major findings and a discussion of future analyses that may become feasible. The appendices contain further details about the demand model.

3 Analysis of Charging Behavior

This section presents statistical analyses of load data and examines important patterns in the data. There is also further analysis of load data done to support the demand modeling in Section 5.

Figure 3-1 presents average weekday EVSE loads for the period August 2011 to June 2012. In general, EVs in the study begin charging immediately after midnight. Loads gradually decline through the night until 6 AM, at which point most EVs have ceased charging and do not charge again until the following night. The slight increase in loads after 11 PM suggests some customers initiate charging prior to midnight. Customers on rates EPEV-H and EPEV-M appear to have nearly identical average EVSE loads, whereas customers on EPEV-L rates have lower average loads after midnight and slightly higher average loads in the evening hours prior to midnight. The total level of charging usage is similar across the three groups. Figure 3-1 is centered at midnight rather than noon to show the peak period more clearly.

Figure 3-1: Average Weekday EVSE Load, by Rate Schedule

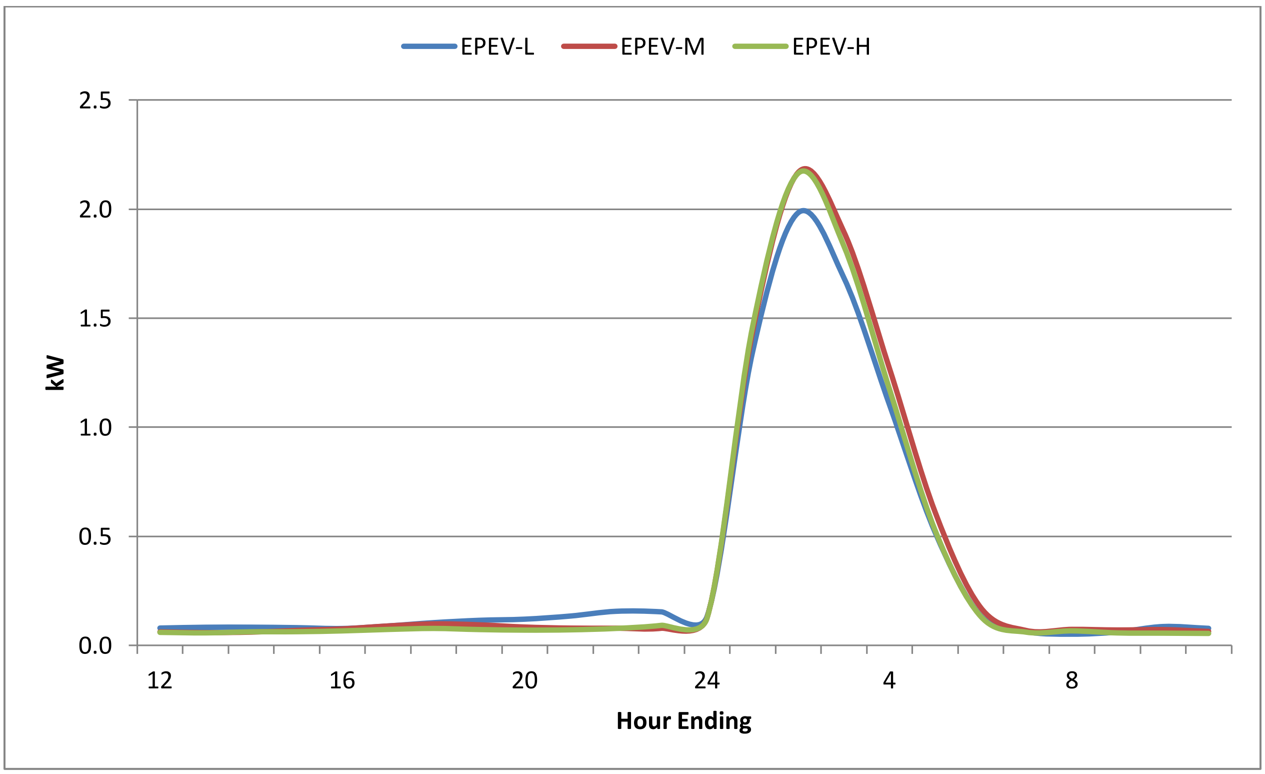


Figure 3-2 shows the same analysis as Figure 3-1, but calculated over weekends rather than weekdays. The basic pattern of charging is almost identical, with lower overall loads.

Figure 3-2: Average Weekend EVSE Load, by Rate Schedule

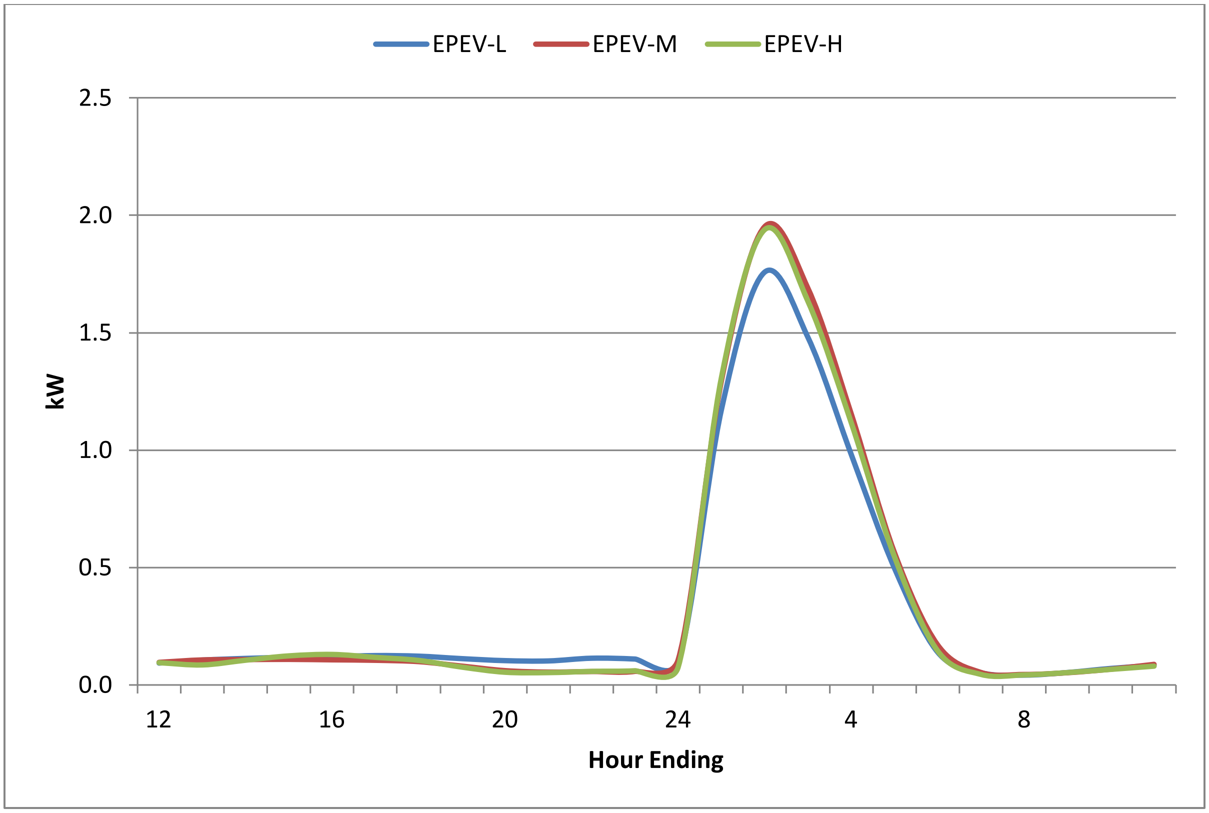
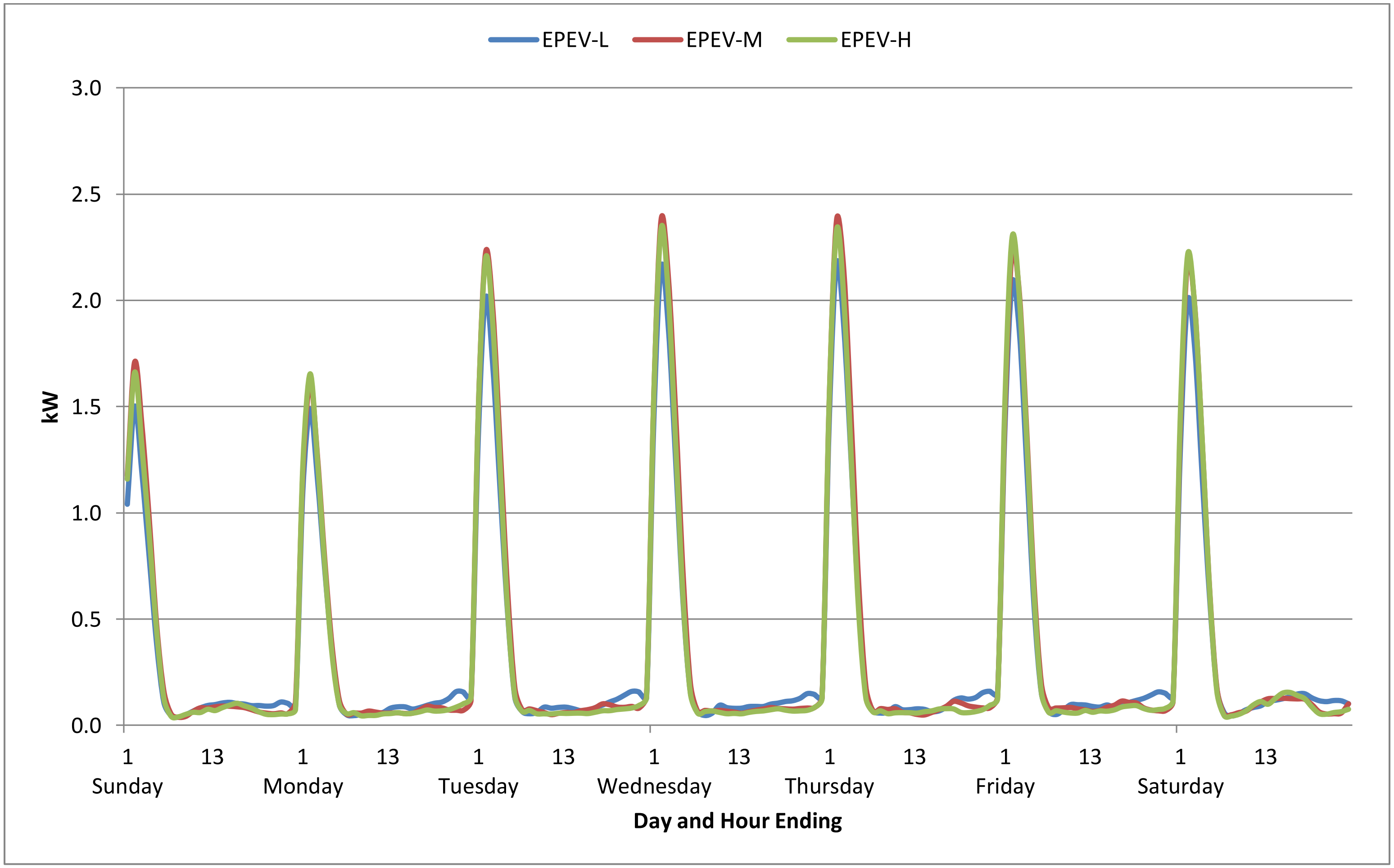


Figure 3-3 shows the same analysis as Figures 3-1 and 3-2, but calculated over individual days of the week separately. The basic pattern of charging is the same over each of the days, but loads are lower on Sundays and Mondays, which probably reflects lower usage of the EV on weekends than on weekdays.

Figure 3-3: Average Daily EVSE Load, by Rate Schedule and Day of Week



Preliminary Results

Figure 3-4 presents the average proportion of daily EVSE loads by rate period for all days in which charging activity occurs.[12] For EPEV-H and EPEV-M customers, 84% and 83% of charging activity occurs during super off-peak hours, respectively. For EPEV-L customers, 78% of charging occurs during super off-peak hours. As shown in Table 5-5 below, the differences in the amount of super off-peak charging between the customers on EPEV-L and the other two rates are statistically significant. This suggests that the lower rates faced by the EPEV-L customers outside of the super off-peak periods makes them more likely to charge during the peak and off-peak hours.

Figure 3-4: Average Proportion of Daily EVSE Energy Consumption by Rate Period

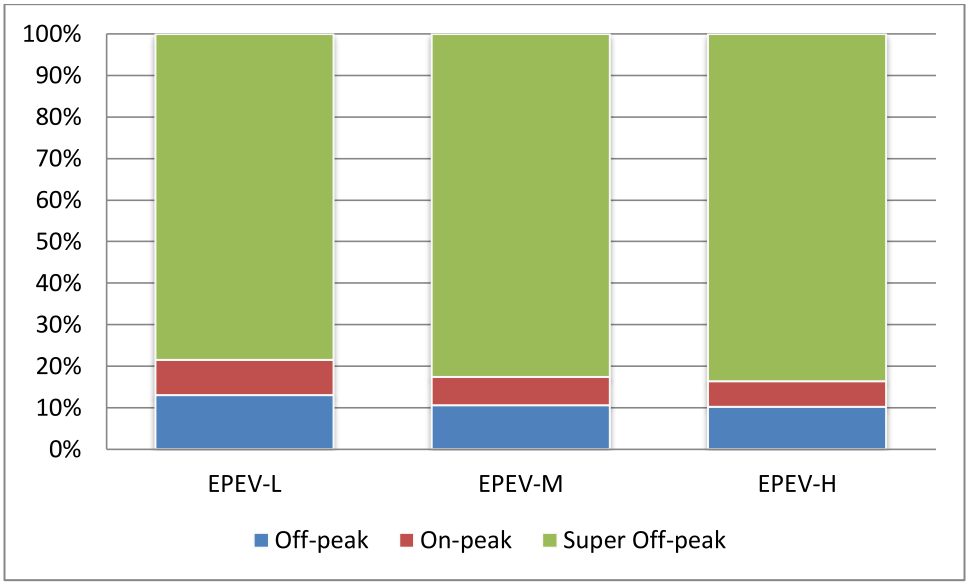


Figure 3-5 presents the average super off-peak proportion of daily EVSE loads by month. While average proportions fluctuate month-to-month, due to a mix of natural variation and new participants joining the study, on average EPEV-L customers persist at slightly lower levels of super off-peak charging.

Figure 3-5 also shows some evidence that customers on different rates are trending toward their expected relative super off-peak consumption over the course of time. For example, customers on the TOU rate with the weakest peak price signal (EPEV-L) have seen the greatest decline in super off-peak's share of usage. At the same time, customers on the TOU rate with the strongest price signal (EPEV-H) have seen the greatest increase in super off-peak share of usage. This may indicate customers are learning about their rates and adapting their behavior; whether this is true or not will become clearer over the next year as additional data is collected for this study.

[12] We exclude all observations where total EVSE consumption over the course of the day is less than 1 kWh.

Figure 3-5: Average Super-off Peak Proportion of Daily EVSE Energy Consumption, by Month

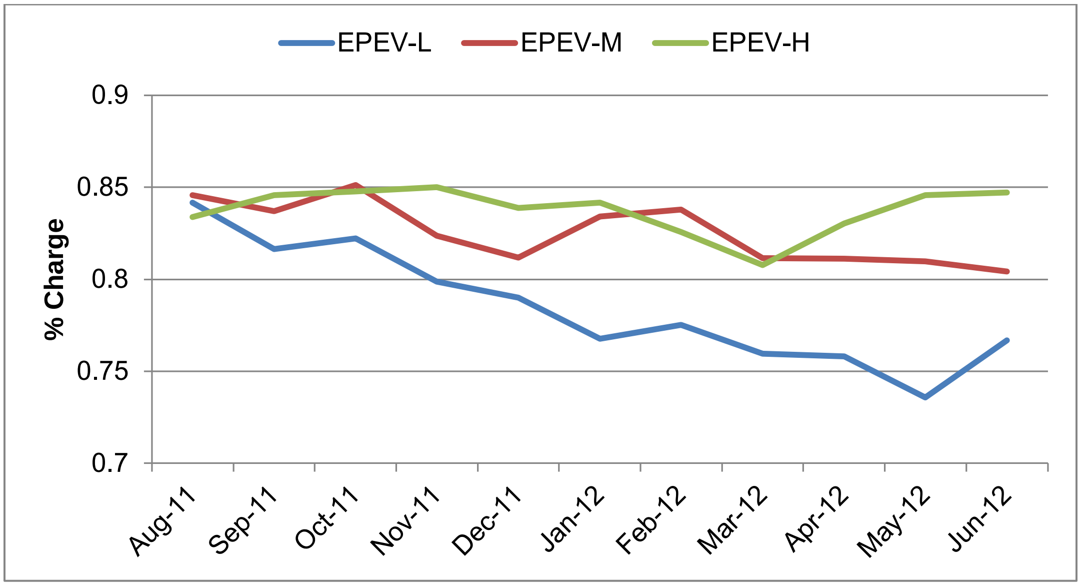


Figure 3-6 presents the average super off-peak proportion of daily EVSE loads by the number of months after the first charging session. This figure is meant to address the problem that Figure 3-5 mixes customers of different tenures in the experiment. Similar to Figure 3-5, Figure 3-6 shows that EPEV-L customers persist at slightly lower levels of super off-peak pricing while customers on the steeper TOU rates increase their super off-peak share of usage.

Figure 3-6: Average Super-Off Peak Proportion of Daily EVSE Energy Consumption, by Months on Rate

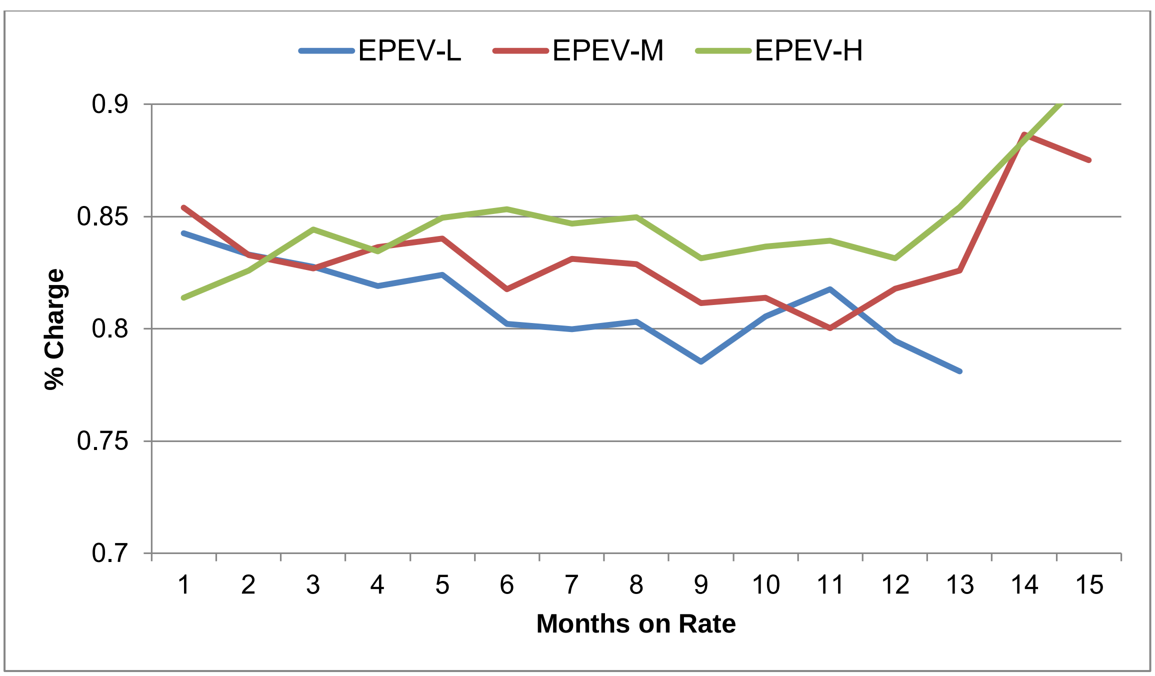


Figure 3-7 presents the median monthly kWh consumption by months after the first charging session. There is no clear trend in any of the values, with all values remaining fairly close to 250 kWh per month throughout the study. Note that not all customers have data available for the full duration of this graph, which means that in Figure 3-7 as "months on rate" increases from left to right, the number of customers observed on the rate in the data decreases.

Figure 3-7: Median Monthly EVSE Energy Consumption, by Months on Rate

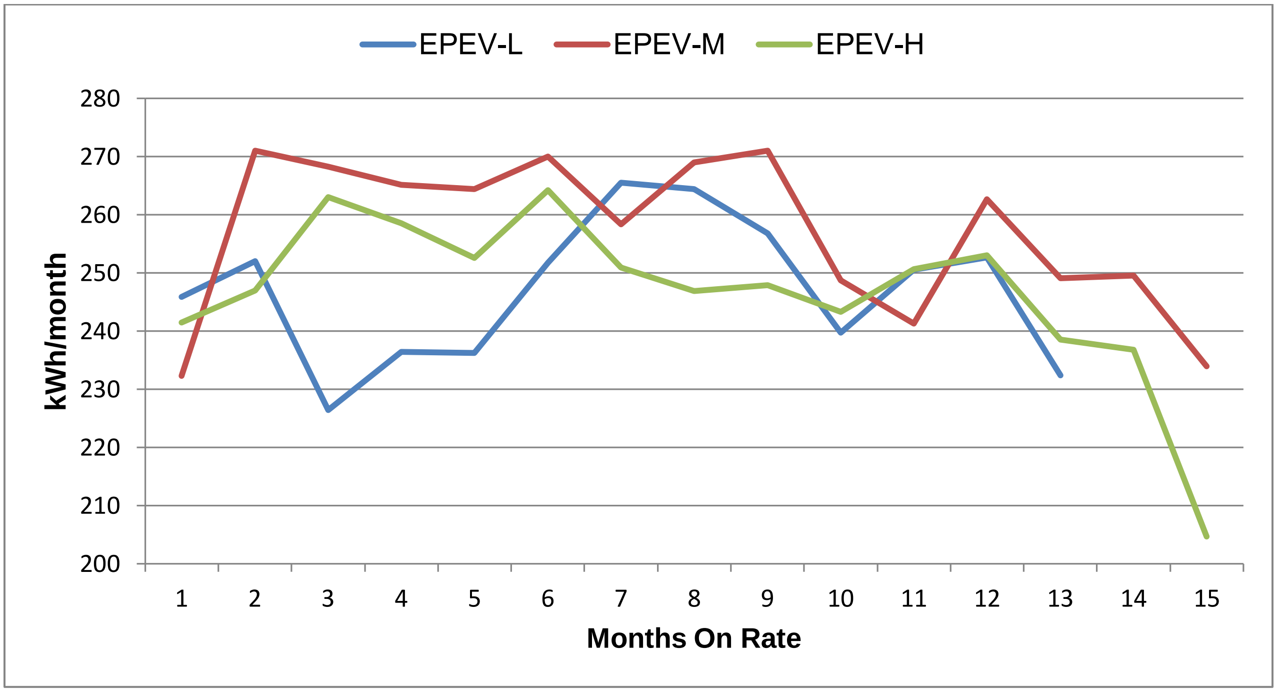


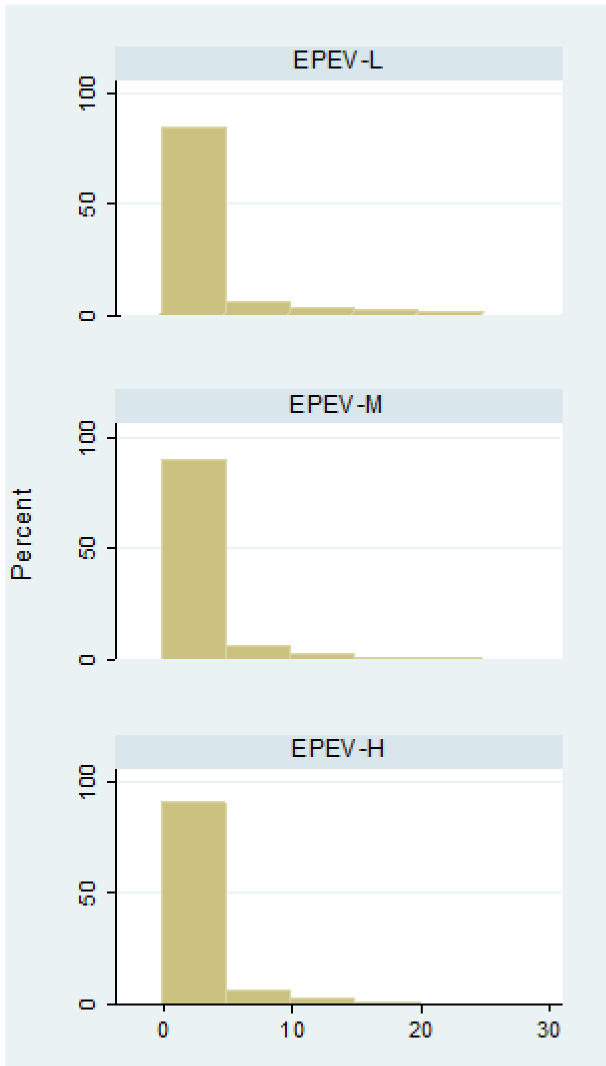
Figure 3-8 addresses whether the differences in super off-peak charging across rates are due to the actions of most customers or just a few customers. The figure presents the distribution across customers of the average number of weekdays per month that 50% or more of EVSE power consumption occurs outside of the super off-peak period.[13] The fact that the bar to the left is the highest on each graph is a consequence of the high amount of super off-peak charging overall.

A notable aspect of Figure 3-8 is that the right tail of the histogram for EPEV-L customers is thicker than for the other two rates. This is because customers are more willing to charge away from the super off-peak period in that group than in the other two groups. However, the difference between the three graphs is mainly due to the behavior of three customers in the EPEV-L group. These three customers' behavior may not be related to the EPEV-L rate, and may instead reflect random characteristics that happened to show up three times among customers on one of the rates. For example, it might be the case that there are few customers on the EPEV-L rate who work away from home late at night, and therefore charge more outside of the super off-peak period. On the other hand, if we had found that the average load shape differences in Figure 3-1 were the result of the small differences in many members of the group, it would be more likely that the observed differences

[13] Days are excluded where total EVSE consumption is less than 1 kWh.

in usage were the result in behavioral changes caused by the TOU rate. However, with the difference due to such a small number of customers, it is impossible to discern whether the average differences in usage are motivated by differences in TOU pricing, or instead result from random variation in the customer population.

Figure 3-8: Distribution Across Customers of the Average Days per Month with a Majority of Charging Outside of Super Off-peak, by Rate Schedule[14]



FSC analyzed EV charger consumption data at 15-minute increments to generate summary information about charging events. For any period in which consumption was greater than 0.1 kWh, the interval was considered part of a charging event. A set of consecutive charging intervals comprises one charging event. Charging events separated by a single 15-minute increment of non-charging were consolidated into one charging event.

[14] The x-axis on the EPEV-H graph is the same axis as on the EPEV-M and EPEV-L graph.

Table 3-1 presents the duration of EVSE charging events. The average charging event lasts approximately two hours and forty-five minutes. Eighty percent of charging events were less than four hours.

Table 3-1: Duration of EVSE Charging Events

Charge Duration	% of Charging Events
0 to 1 hr	19%
1 to 2 hrs	19%
2 to 3 hrs	22%
3 to 4 hrs	20%
4 to 5 hrs	14%
5 to 6 hrs	4%
6+ hrs	1%

Overall, the statistical analysis of charging behavior continues to show a strong tendency for super off-peak charging. This indicates that customers are substituting electricity usage in other periods to the super off-peak period in response to the incentives of all of the TOU rates. Furthermore, customers on the TOU rate with the weakest price signal (EPEV-L) are charging more outside of the super off-peak period when compared to the customers on the TOU rates with stronger price signals (EPEV-M and EPEV-H). This is evidence that the degree to which customers respond to the TOU rate depends on the price signal strength (peak to off-peak ratio) of the rate.

There is also some evidence that customer behavior is changing over time. Customers on EPEV-L have seen the largest decrease in the super off-peak usage over time. In addition, customers on EPEV-H have seen the biggest increase in the super off-peak usage over time. This might indicate that customers learn more about their rates over time, and are behaving more like we would expect in the long run. Another possibility is that customers with weaker TOU rates are becoming relatively less reliant on the use of the EVSE or EV charging timer over time. If true, it would probably lead to more charging outside of the super off-peak period. Currently, these differences between the charging patterns of customers on the different rates are due to the actions of a small number of participants, and it will be important to observe whether these differences persist over time.

4 Linking Charging Behavior to Survey Responses

This section presents findings on survey responses associated with charging behavior. In November 2011, SDG&E invited participants in the rate experiment to participate in a survey of customer knowledge, behavior and attitudes related to EV use and charging.

Approximately 476 participants were sent mail or email invitations. Approximately 121 participants were not sent invitations due to their stated desire to opt-out of SDG&E related survey or marketing activities. Participants completed the survey by following a URL link to a survey website hosted by Vision Critical. A unique participant code was used to link a participant's survey responses with their usage data. Follow-up invitations were sent approximately one week after the initial invitation, as a reminder.

There were 205 customers who responded to the survey and the interim report extensively documented responses to the survey.[15] Since that analysis took place, however, FSC can now link survey responses to EVSE charging and whole-house load data. Out of the 205 survey participants, 156 of them can be linked to whole-house load data and 102 can be linked to EVSE charging data. A few analyses are provided below that further examine survey results in light of this new link. These analyses corroborate the results of the survey, indicating that survey responses are consistent with metered load data.

Figure 4-1 shows the average daily load profiles for three groups of customers, divided according to their self-reported percentage of home charging activity. For example, the red line in the graph corresponds to the 50 survey participants who reported engaging in 95% or more of their charging while at home. According to the interval data, participants who indicate that they do most of their charging while at home in their survey responses have greater average daily usage than participants who indicate that they charge at charging stations away from home in their survey responses.

[15] See "Interim Report for San Diego Gas & Electric's Electric Vehicle Pilot" prepared for SDG&E by The FSC Group.

Figure 4-1: Average Survey Participant Load Profiles by Reported Percent of Charging Activity at Home

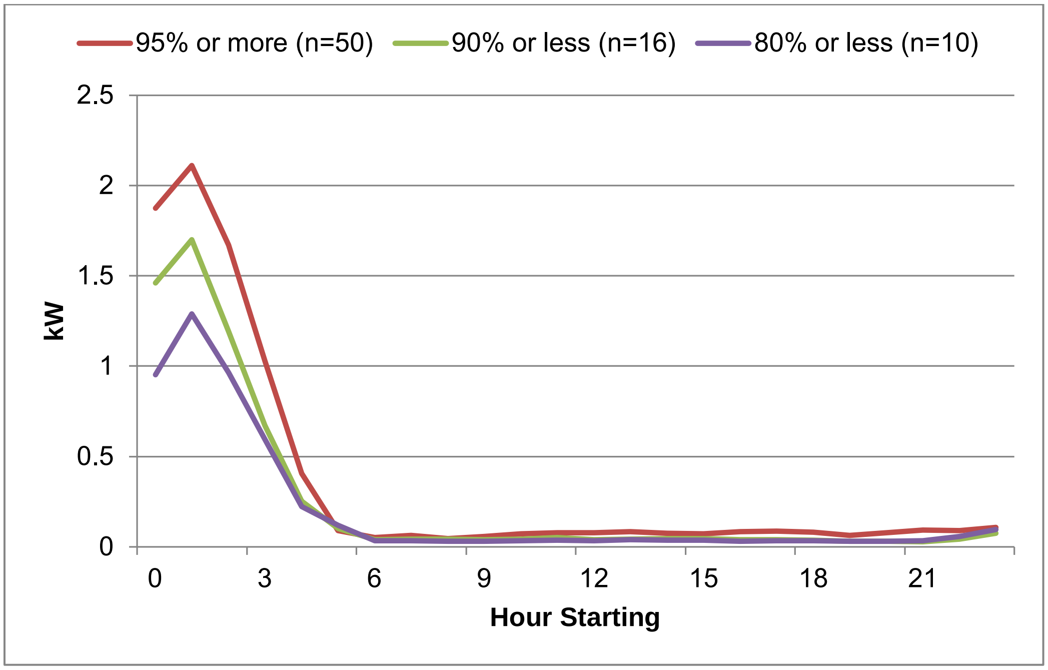


Table 4-1 shows average demand categorized by the percentage of home charging activity and TOU period. The basic pattern shown in Figure 4-1 arises here as well. Customers with lower proportions of at-home charging have lower levels of off-peak and peak charging as well as super off-peak charging.

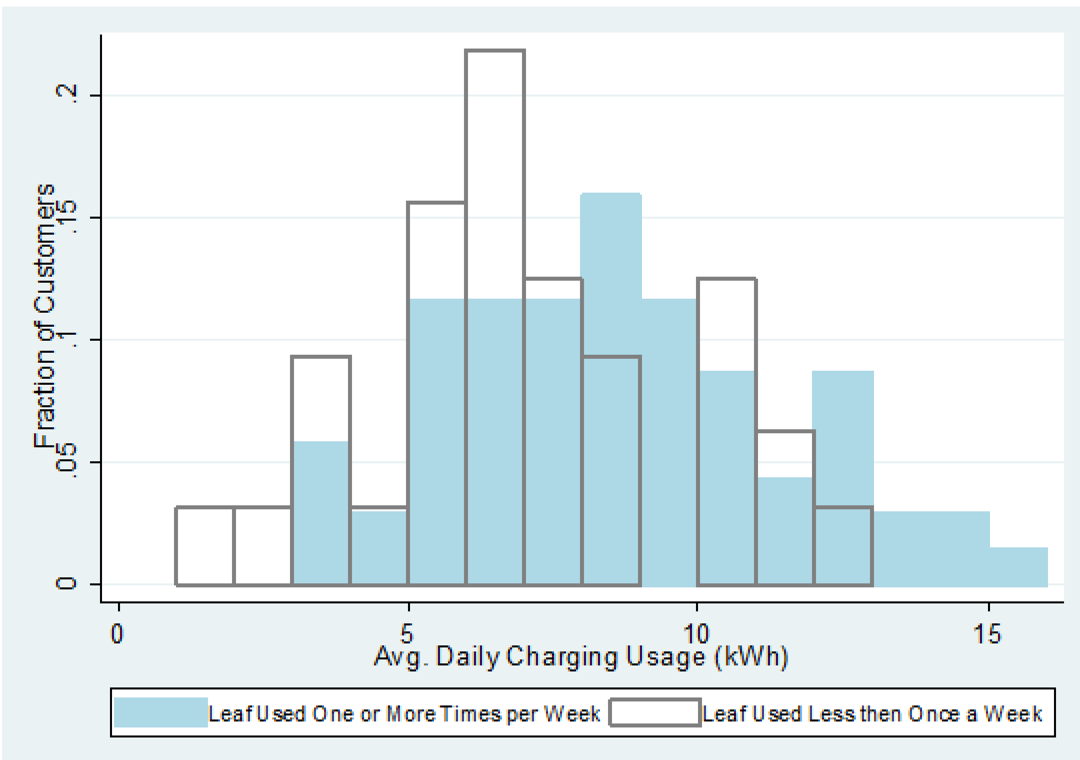
Table 4-1: Average Survey Participant TOU Period Demand (kW) by Percent of Charging Activity at Home

TOU Period	95% or more	90% or less	80% or less
Super Off Peak	1.42	1.06	0.80
Off Peak	0.08	0.05	0.05
Peak	0.08	0.04	0.03

One of the survey questions asked participants to indicate if they use the timer on their EVSE or EV. The customers who used the timer were asked the start and end times during which they set the timer. FSC examined the interval data of the 89 survey participants who indicated that they used the timer to determine if most of their charging activity took place during the time period set by the participants. Based on EVSE charging data, these respondents engage in 86% of their total charging during the time periods they indicated on the survey, indicating both that these respondents responded accurately and that they do the vast majority of their charging with the timer.

Another survey question asked participants how often they used the LEAF for driving to work or school, short trips around town, vacations, long trips, business or work use. FSC categorized participants into two groups – those who stated they use the LEAF more than once per week and those who stated they use it less than once per week, averaged across all activities. Figure 4-2 is a histogram of the average daily usage of participants across both of these categories. As expected, the distribution of usage of participants who use the LEAF less than once per week is centered left of the distribution of usage of participants who use it more than once per week. This shows that the more frequent users of the LEAF also charge more frequently, as expected, and it further corroborates the results of the survey. The average daily charging usage for customers who use the LEAF one or more times per week is 8.27 kWh, while the average daily charging usage for customers who use the LEAF less than once per week is 6.93 kWh. These values correspond to the mean values of the distributions shown in Figure 4-2.

Figure 4-2: Distribution of Avg. Daily Survey Participant Charging Usage By Customers Who Use the LEAF More than Once a Week (n=69) and Customers Who Use it Less than Once a Week (n=32)



Based on these three results, participants in the study generally behaved as they indicated with their survey responses. This is a useful finding since it is rare that we have the opportunity to corroborate survey responses with independently measured data on respondents.

The survey also asked participants for several demographic characteristics. Table 4-2 shows average daily usage and maximum demand on the average day for participants by various demographics. Maximum demand on the average day is determined by first taking the average of each customer's loads over each hour of each weekday. We then take the maximum of those hourly averages for each customer and call that the maximum demand on the average day. The table then shows the average value of those maximums across customers within each category. The metric is meant to reflect a customer's typical maximum usage on a weekday.

Although there are some differences in daily usage and maximum demand across different demographics, no strong trends emerge. For example, respondents aged 35-44 have higher daily average usage than those aged 25-34, but they also have higher usage than those aged 45-54, showing that there is no strong relationship between age and usage. Similar points hold for income and education levels.

Table 4-2: Usage by Demographic Characteristics from Survey Participant Load Profiles

Demographic Characteristic	Avg. Daily Usage (kWh)	Maximum Demand on the Average Day (kW)	Number of Customers
Gender			
Male	7.89	2.20	78
Female	8.89	2.34	19
Decline to State	9.18	2.38	1
Age			
25 – 34	7.21	1.92	5
35 – 44	9.47	2.39	24
45 – 54	8.29	2.32	32
55 – 64	6.88	2.06	26
65 or Older	7.67	2.12	10
Decline to State	9.18	2.38	1
Education			
High School	8.41	2.37	1
Some College	7.95	2.08	5
Graduated College	8.10	2.23	43
Graduate School	8.08	2.24	48
Decline to State	9.18	2.38	1
Income (1,000 $'s)			
Less than 50	10.00	3.04	1
50 – 75	9.14	2.23	4
75 – 100	7.69	2.04	8
100 – 125	7.80	2.15	8
125 – 150	8.39	2.39	15
150 – 175	8.12	2.38	13
175 – 200	9.46	2.32	3
More than 200	8.46	2.35	19
Decline to State	7.50	2.02	27

In addition to overall usage, it is of interest whether any demographic groups show a propensity for super off-peak charging. To address this, Tables 4-3 through 4-5 illustrate the average customer's share of super off-peak usage relative to total usage across different demographic categories. Although there is some variation across demographic groups, no strong patterns emerge.

Table 4-3: Usage Ratios by Age from Survey Participant Load Profiles

Age	Ratio of Avg. Hourly Super Off-peak Usage to Avg. Hourly Usage	Percent of Customers			Number of Customers
		EPEV-L	EPEV-M	EPEV-H	
25 - 34	0.66	20	60	20	5
35 - 44	0.70	21	42	38	24
45 - 54	0.72	19	38	44	32
55 - 64	0.66	27	31	42	26
65 or Older	0.69	20	30	50	10
Decline to State	0.70	0	100	0	1

Table 4-4: Usage Ratios by Education from Survey Participant Load Profiles

Education	Ratio of Avg. Hourly Super Off-peak Usage to Avg. Hourly Usage	Percent of Customers			Number of Customers
		EPEV-L	EPEV-M	EPEV-H	
High School	0.73	0	100	0	1
Some College	0.65	40	20	40	5
Graduated College	0.69	23	33	44	43
Graduate School	0.70	19	42	40	48
Decline to State	0.70	0	100	0	1

Table 4-5: Usage Ratios by Income from Survey Participant Load Profiles

Income	Ratio of Avg. Hourly Super Off-peak Usage to Avg. Hourly Usage	Percent of Customers			Number of Customers
		EPEV-L	EPEV-M	EPEV-H	
Less than 50	0.86	0	0	100	1
50 - 75	0.68	25	50	25	4
75 - 100	0.63	38	38	25	8
100 - 125	0.70	0	50	50	8
125 - 150	0.67	20	47	33	15
150 - 175	0.78	31	23	46	13
175 - 200	0.67	0	67	33	3
More than 200	0.71	11	42	47	19
Decline to State	0.66	30	30	41	27

These demographic analyses of charging demand show that demand characteristics are relatively constant across a wide range of incomes, educations and ages. This is a useful finding because it suggests that charging patterns are driven by unobservable characteristics that are not strongly correlated with demographics. In this case, it also further corroborates the idea that the presence of the timer, in conjunction with the TOU pricing, is sufficient to strongly influence charging patterns despite major differences in customer characteristics.

5 Electricity Demand Model

Although the descriptive graphs and statistics of charging load are highly informative about participant behavior, much of the audience for this pilot's results will be interested in understanding how the results could be extrapolated to other populations and other TOU pricing structures. To perform such an extrapolation requires a model of demand for EV charging. The primary output of such a model will be estimates of elasticities of demand, which are a way of summarizing how demand would respond to a range of pricing schedules.

This section describes the methodology for estimating an economic demand model of charging within the EV Pilot. First, we describe the structural model to be used for the analysis: a system of electricity demand equations derived from a generalized Leontief cost function. Second, we describe the estimation procedure: non-linear seemingly unrelated regression. Finally, we present results from the estimation and put them into a broader context.

5.1 Model

In order to estimate the effects of TOU pricing with the available data we need to model electricity demand within a theoretical framework. This framework allows us to interpret the raw data we see as the output of a decision process being made by the household. The decision facing a household at any given time is whether to charge the LEAF now or to charge it later. This decision will be affected by many factors, including the price of charging now and charging later, as well as household-specific factors, such as the need for use of a vehicle at the moment and the current state of charge in the vehicle. The prices affecting this decision are known and enter the model directly. Although the household-specific factors are also important to the charging decision, we cannot observe them and so they cannot be modeled specifically. These factors enter the model by causing unexplained variation around charging behavior that the model would predict based on price alone.

Focusing on the price-related aspects of the EV charging decision, the household must make a trade-off between paying the price to charge now and paying a possibly different price to charge later. In this case, that is the trade-off between charging during on-peak, off-peak and super off-peak periods. We define a set of parameters that determine how households make these tradeoffs and we refer to them as elasticities. An elasticity defines how much one quantity changes in response to a change in another quantity. Specifically, elasticities are expressed as what the expected percentage change of one quantity is with respect to the expected percentage change of another quantity.

In this case, the relevant elasticities are those that tell us how the quantity of EV charging during one period changes when the price of EV charging changes during that period (own-price elasticity) or during another period (cross-price elasticity). It is important to recognize that how much a household charges at any time is determined both by how much it costs at that time and by how much it costs at other times. For example, charging right now for $0.35/kWh might be quite unattractive if the price one hour from now is $0.15/kWh and might be quite attractive if the price one hour from now is $0.75/kWh. So, a household's charging at any given time is determined by the entire price schedule that the household faces, rather than just by the current price.

Elasticities of demand can be defined and estimated for virtually any good that consumers buy. Therefore, it is possible to interpret the elasticities estimated for this pilot in the context of elasticities of demand for other consumer goods. Elasticities of demand are influenced by a number of factors:

- Availability of substitutes: customers will be more sensitive to changes in price (more elastic) with the availability of close substitutes;
- Percentage of income: customers will be more sensitive to the price of a good the higher the price is in terms of the percentage of a typical customer's income;
- Necessity: customers will be less sensitive to price if a good is a necessity; and
- Duration: customers will be more sensitive to price in the long run, as it gives them more time to change behavior.

Table 5-1 provides examples of the own-price elasticity of demand for a number of goods. The way to interpret these values is that they indicate by what percentage the quantity demanded will change for a percentage change in price. Own-price elasticities generally have a negative sign, indicating that a price increase will result in a demand decrease. For example, the value of -0.1 for salt tells us that for every 1% increase in the price of salt, the quantity demanded will fall by 0.1%. Elasticities are generally considered according to their absolute values, so values closer to zero indicate items that have lower elasticities or have more inelastic demand. In general, items on the list that are necessities (such as salt) and that have no close substitutes (such as coffee) have elasticities much closer to zero (i.e., lower) than items that are luxuries (such as restaurant meals) and items that have close substitutes (such as Chevrolets).

Table 5-1: Example Elasticities[16]

Product	Elasticity
Salt	-0.1
Coffee	-0.3
Daily Electricity	-0.3 to -0.5
Fish (cod) consumed at home	-0.5
Taxi, short-run	-0.6
Movies	-0.9
Housing, owner occupied	-1.2
Private education	-1.1
Radio and television receivers	-1.2
Restaurant meals	-2.3
Foreign travel, long-run	-4.0
Chevrolet automobiles	-4.0
Fresh tomatoes	-4.6

[16] Elasticities in this table were taken from http://welkerswikinomics.wetpaint.com/page/PED+for+Various+Products. The original sources are: Economics: Private and Public Choice, James D. Gwartney and Richard L. Stroup, eighth edition 1997, seventh edition 1995; primary sources: Hendrick S. Houthakker and Lester D. Taylor, Consumer Demand in the United States, 1929-1970 (Cambridge: Harvard University Press, 1966,1970); Douglas R. Bohi, Analyzing Demand Behavior (Baltimore: Johns Hopkins University Press, 1981); Hsaing-tai Cheng and Oral Capps, Jr., "Demand for Fish" American Journal of Agricultural Economics, August 1988; and U.S. Department of Agriculture.

The model in this analysis defines the elasticities that determine a household's charging behavior as follows:

- ϵ_{p-p}: The elasticity of on-peak charging with respect to the price of on-peak charging. This quantity tells us how much we expect the quantity of on-peak charging to change when the price of on-peak charging changes. This is also referred to as the own-price elasticity of on-peak charging. The elasticity of off-peak charging with respect to its price and the elasticity of super off-peak charging with respect to its price have similar interpretations and are denoted by ϵ_{op-op} and $\epsilon_{sop-sop}$, respectively, where the *op* subscript refers to the off-peak period and *sop* refers to the super off-peak period;
- ϵ_{p-op}: The elasticity of on-peak charging with respect to the price of off-peak charging. This quantity tells us how much we expect the quantity of on-peak charging to change when the price of off-peak charging changes. This is referred to as a cross-price elasticity; and
- ϵ_{op-p}: The elasticity of off-peak charging with respect to the price of on-peak charging. This is another cross-price elasticity. The remaining cross-price elasticities are denoted similarly: ϵ_{sop-p}, ϵ_{p-sop}, ϵ_{op-sop}, and ϵ_{sop-op}. The notation can be somewhat confusing in that it is easy to note the double subscript and to think of these values as second derivatives. This is incorrect; the elasticities are first derivatives of a demand level with respect to a price level. Consequently, cross-price elasticities are not necessarily symmetric; for example, it is not necessarily the case that $\epsilon_{op-p} = \epsilon_{p-op}$. In fact, that will be true only rarely.

We have defined the elasticities as applying to charging during the TOU time periods. However, household decision-making probably takes place at a more granular level of time; households decide not only between charging during peak and off-peak periods, but also between charging at 2 PM and 3 PM, for example. However, the pricing experiment analyzed here only allows us to model decision-making over the TOU time blocks because those are the only time periods over which we observe different sets of prices. There are no customers in the experiment who face different prices at 2 PM than at 3 PM, so we cannot make any inference about how customers respond to different prices at those times.

To estimate the elasticities listed above, we now turn to the theoretical framework we referred to at the beginning of this section. We model the household as a unit or agent that produces many outputs. These outputs jointly contribute to the household's utility or well-being. We focus on one output in particular: the usage of an EV and the value of this output as a function of a set of inputs. Although it is the case that the household's use of an EV contributes to well-being in a way that depends on many other factors in the household, we lack sufficient data on each household to model this aspect of the problem. Instead, we suppose that the household's EV charging decisions are separable from its decisions to consume other goods and services. This means that we can model EV charging decisions separately from other household decisions. This strong assumption is virtually always used in demand modeling and is a result of the limited data available to modelers.

Using this framework, the inputs of household production become the electricity used in each of the pricing periods: peak, off-peak and super off-peak. We then hypothesize a cost function that arises from the solution of the optimal production that can be achieved under any set of prices. We estimate the parameters of the cost function using load data and the price variation across customers in the pilot. We then derive elasticities and calculate the impacts of the TOU rates using the estimated parameters of the cost function.

We model the energy used for EV charging with a generalized Leontief (GL) production function. The model we use is essentially a special case of the model presented in Aigner, Newman and Tishler (1994)[17], which is used to examine non-residential TOU rates in Israel. We use the case of the model with three period pricing: peak, off-peak and super off-peak.

The foundation of the model is the assumption that the household has a cost function where total household production and electricity prices during different periods of the day are inputs.[18] A cost function expresses the lowest cost at which a household can achieve a given level of production under a given set of prices. For any given set of prices, there is an optimal amount of production (and therefore utility) that the household can achieve. That production level has an associated cost at the given prices, which defines the cost function.

The cost function is defined such that the cost (C) is a function of output (y), prices ($\mathrm{p_i}$ for $\mathrm{i} = 1,2,3$), and parameters (β_{ij} for $\mathrm{i,j} = 1,2,3$). [19]

$$\mathrm{C} = \mathrm{y}\sum_{i=1}^{3} \sum_{j=1}^{3} \beta_{\mathrm{ij}}\left(\mathrm{p_i p_j}\right)^{1/2} \qquad (1)$$

The data is then used to estimate the parameters of this function by deriving share equations for each period's share of usage (m_i) as a percentage of total average usage.[20]

$$m_i = \frac{\sum_j \beta_{\mathrm{ij}}\left(\mathrm{p_i p_j}\right)^{1/2}}{\sum_k \sum_j \beta_{\mathrm{kj}}\left(\mathrm{p_k p_j}\right)^{1/2}} \qquad i = 1,2,3 \qquad (2)$$

In equation (2) the *j* and *k* indices each go from 1 to 3. Together, these share equations make up a system of seemingly unrelated regressions (SUR). The estimation of the SUR is done in STATA, using the *nlsur* function, which fits a system of nonlinear equations by feasible, generalized nonlinear least squares (FGNLS).

The estimated parameters are those that minimize the squared difference between the predicted and actual share for each month of each customer. From these estimated parameters, we calculate the own-price elasticities:

$$\epsilon_{ii} = \frac{1}{2}\left[\frac{\beta_{\mathrm{ii}}}{\sum_{kj} \beta_{\mathrm{ik}} \mathrm{p_k^{1/2}} \mathrm{p_i^{-1/2}}} - 1\right] \qquad i = 1,2,3 \qquad (3)$$

[17] Aigner, D. J., J. Newman and A. Tishler. "The Response of Small and Medium-size Business Customers to Time-of-Use (TOU) Electricity Rates in Israel." Journal of Applied Econometrics. (1994).

[18] A detailed description of the derivation of model is included in Appendix A.

[19] To keep notation simple in the model development we use 1, 2, 3 to denote the peak, off-peak and super off-peak periods, respectively, rather than p, op and sop.

[20] Note that the model does not differentiate among days and therefore within the model there is no difference between average usage shares at a daily level and average usage shares at a monthly level (as long as the distinction between weekends and weekdays is handled consistently). The model is estimated on monthly usage shares.

and cross price elasticities:

$$\epsilon_{ij} = \frac{1}{2}\frac{\beta_{ij} p_j^{1/2} p_i^{-1/2}}{\sum_k \beta_{ik} p_k^{1/2} p_i^{-1/2}} \qquad i \neq j \qquad (4)$$

These elasticities correspond to those defined above. In both (3) and (4), the *k* index goes from 1 to 3.

5.2 Data

The data comes from 387 customers on the experimental TOU rates. The data covers the period from January 2011 until June 2012. The data originates as 15-minute interval measurements of kWh. The electricity rates from Table 2-2 are used as the prices in the model. The interval data is then converted into monthly shares of on-peak, off-peak and super off-peak consumption, by customer, as a fraction of total monthly usage respectively. Appendix B shows results for alternative choices of data as model inputs.

A good first step in analyzing experimental results is to assess the validity of the experiment. In this case, a crucial part of the experiment is that customers who opt to be part of the pricing experiment are randomly assigned to one of three rates. It is important therefore to assess whether that random assignment has been achieved without any selection bias entering the experiment. To address this, Table 5-2 shows the results of a validation exercise that demonstrates the successful randomization of customers onto the three different TOU rates. The table shows counts of customers with given observed characteristics across the three rates to demonstrate that the distributions of these characteristics are similar within each TOU rate. The observed characteristics in the table are climate zone, reported age from the survey, reported education, reported income and whether or not a customer responded to the survey.[21] The table shows both raw counts for each TOU rate within each characteristic category and the percentage of customers on each rate with that characteristic. As the table shows, in general, the distribution of each characteristic is similar across each of the rates.

Table 5-2 also shows the results of a statistical test that tells us whether there is any evidence that the distribution of a given characteristic is correlated with the TOU rates. This test is known as Fisher's exact test, and it is a common way of judging whether distributions of two variables are correlated within a population. In this case, small values in the far right column of the table would be evidence that there was a meaningful correlation between the distribution of the characteristic in the population and the TOU rate. This would be possible evidence that some type of selection bias had entered the experiment. Generally, values below 0.05 would be cause for further investigation. In this case, all values are above 0.2, indicating that there is no evidence of selection bias.

[21] Ideally, this table would also include a measure of usage from prior to the start of the pilot, and that may be included in subsequent analyses.

Table 5-2: Distributions of Characteristics Across Experimental Rates

Characteristic	Category	Count of Customers with Characteristic on Each Rate			Percentage of Customers On Rate with Characteristic			Fisher's Exact Probability
		EPEV-L	EPEV-M	EPEV-H	EPEV-L	EPEV-M	EPEV-H	
Climate Zone	Coastal	69	79	77	64	55	58	0.35
	Inland	39	65	56	36	45	42	
Age	25 - 34	1	3	1	5	8	3	0.89
	35 - 44	5	10	9	24	27	23	
	45 - 54	6	12	14	29	32	35	
	55 - 64	7	8	11	33	22	28	
	65 or Older	2	3	5	10	8	13	
	Decline to State	0	1	0	0	3	0	
Education	High School	0	1	0	0	3	0	0.78
	Some College	2	1	2	10	3	5	
	Graduated College	10	14	19	48	38	48	
	Graduate School	9	20	19	43	54	48	
	Decline to State	0	1	0	0	3	0	
Annual Income ($k)	Less than 50	0	0	1	0	0	3	0.68
	50 - 75	1	2	1	5	5	3	
	75 - 100	3	3	2	14	8	5	
	100 - 125	0	4	4	0	11	10	
	125 - 150	3	7	5	14	19	13	
	150 - 175	4	3	6	19	8	15	
	175 - 200	0	2	1	0	5	3	
	More than 200	2	8	9	10	22	23	
	Decline to State	8	8	11	38	22	28	
Survey Response	Yes	23	37	42	21	26	31	0.22
	No	85	106	94	79	74	69	

Table 5-3 shows the average usage in each period by rate group on weekdays and Table 5-4 shows the same for weekends. As was shown in Figures 3-1 and 3-2, the basic pattern is the same in each table, with the vast majority of charging occurring during the super off-peak period for all groups on both weekdays and weekends.

Table 5-3: Average Weekday Demand for Each Period by Rate

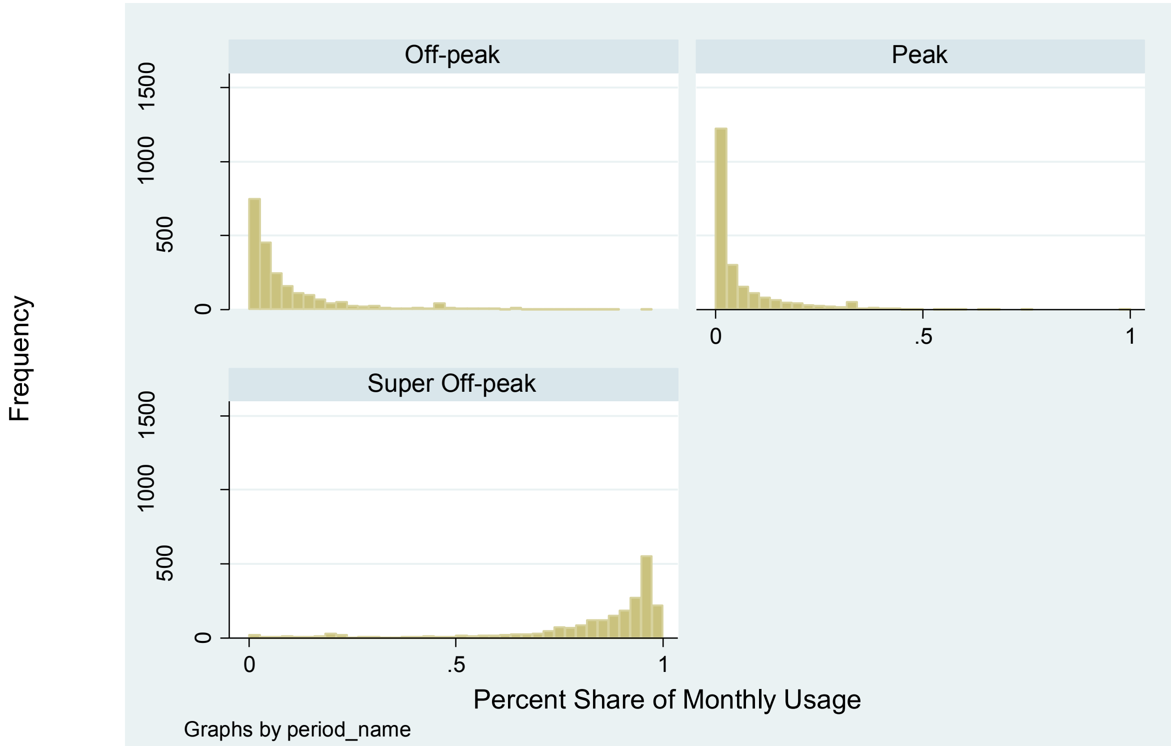
Rates	Average kW by Period		
	Peak	Off-peak	Super Off-Peak
EPEV-L	0.10	0.11	1.28
EPEV-M	0.09	0.09	1.44
EPEV-H	0.07	0.08	1.41

Table 5-4: Average Weekend Demand for Each Period by Rate

Rates	Average kW by Period		
	Peak	Off-peak	Super Off-Peak
EPEV-L	0.13	0.09	1.14
EPEV-M	0.11	0.08	1.29
EPEV-H	0.10	0.07	1.29

Figure 5-1 shows the histograms of observations of share by rate period for each customer-month included in the study. As the histograms show, the share of super off-peak charging is much higher than the share of peak and off-peak charging.

Figure 5-1: Histograms of Percent Shares of Monthly Usage



Over the time frame that data was collected a significant number of new customers enrolled each month. Therefore, if a customer did not have more than three days of data in their first month of enrollment, that month was dropped from the analysis.

Table 5-5 presents the results of a comparison of means for the peak period, off-peak period and super off-peak period usage for all pair-wise combinations of the TOU rates. A comparison of means is a statistical method that allows us to test the hypothesis that the difference in mean usage in the peak period between the customers with different rates is different than zero. Statistically significant differences are indicated by p-values less than 0.05. One minus the p-value indicates the confidence level for rejecting the null hypothesis of no difference between groups. For example, the results for weekdays indicate that the differences in peak period usage between customers on EPEV-H and EPEV-M are statistically significant at a level of 99%. The table shows values calculated over all days. Most of the pair-wise differences are statistically significant.

Table 5-5: Peak Period Pair-wise Comparison of Means

Day Type	Rates Compared	Mean On-Peak kWh Difference	P-Value	Mean Off-Peak kWh Difference	P-Value	Mean Super Off-Peak kWh Difference	P-Value
Weekdays	EPEVL-EPEVM	0.010	0.20	0.022	0.01*	0.163	0.00*
	EPEVL-EPEVH	0.029	0.00*	0.032	0.00*	0.133	0.01*
	EPEVM-EPEVH	0.018	0.01*	0.010	0.10	0.030	0.50
Weekends	EPEVL-EPEVM	0.019	0.01*	0.014	0.02*	0.150	0.00*
	EPEVL-EPEVH	0.027	0.00*	0.024	0.00*	0.146	0.00*
	EPEVM-EPEVH	0.008	0.22	0.010	0.03*	0.005	0.91

*P-values with asterisks indicate results significant at a 95% confidence value (i.e., p-values less than 5%)

5.3 Results

Table 5-6 presents the estimates of the β coefficients for the model. Separate models were estimated for weekdays and weekends, and the table shows sets of values calculated based on each. The reason for this separate weekday and weekend modeling is that we might expect that a household's decisions about charging would be quite different on weekends than it would be on weekdays. The parameter estimates in the table all have quite low standard errors and fairly small confidence intervals. The parameters for the weekday model are quite similar to the parameters for the weekend model. In fact, none of the weekend parameters are different from the weekday parameters at a 95% confidence level, despite the fact that all the parameter estimates have low standard errors. Only two of them (β_{11} and β_{13}) are different at an 80% confidence level, which is close to what would be expected due to random variation alone even if there were no systematic differences in customer behavior on weekends. This is not surprising given the results shown in Tables 5-3 and 5-4, which indicate that average charging patterns are quite similar between weekends and weekdays. For this reason, we focus on weekday results for the remainder of this section, recognizing that weekend results are not very different.

Table 5-6: Model Coefficient Estimates

Weekend/ Weekday	Parameter	Coefficient	Std. Err.	95% Confidence Interval	
Weekday	β_{11}	-0.014	0.001	-0.016	-0.011
	β_{12}	-0.008	0.003	-0.013	-0.003
	β_{13}	0.059	0.004	0.052	0.066
	β_{22}	-0.036	0.007	-0.049	-0.024
	β_{23}	0.113	0.008	0.098	0.128
	β_{33}	0.221	0.013	0.196	0.247
Weekend	β_{11}	-0.020	0.002	-0.024	-0.016
	β_{12}	-0.004	0.003	-0.010	0.002
	β_{13}	0.077	0.005	0.067	0.086
	β_{22}	-0.044	0.008	-0.059	-0.029
	β_{23}	0.120	0.008	0.105	0.136
	β_{33}	0.178	0.013	0.152	0.204

Recall, these parameters are estimated pieces of the cost function, they are not elasticity estimates. However, with these estimates we can derive the own-price elasticities and cross-price elasticities for each period.

Intuitively, all of the own-price elasticities should be negative, and all of the cross-price elasticities should be positive. Negative own-price elasticities (such as those shown in Table 5-1) indicate that the demand for electricity falls as the price increases. Positive cross-price elasticities indicate that two inputs are substitutes. This means that as the price of electricity increases during one time period, the demand for electricity increases in another period. Conversely, negative cross-price elasticities would indicate that goods are complements. This means that as the price of electricity increases during one time period, the demand for electricity decreases in another period. We would not expect that to be the case with EV charging because we expect that a household has a fairly stable need for charging each day and that mainly they adjust by changing the time of day that they charge.

Table 5-7 shows the elasticity estimates for the weekday model.[22] Note that the elasticity formulas vary with price, so even though the estimated cost function parameters are constant across customers and across time, the elasticities themselves vary across both. Although standard errors are not shown, all of the elasticity estimates, with the exception of ϵ_{op-p}, are significantly different from zero at a 99% confidence level. The own-price elasticities are all negative, which is expected; because an increase in the price of an input should cause a decrease in demand.

The charging load shapes shown in Figures 3-1 through 3-3 are quite different from those associated with a typical whole-house residential TOU rate. Currently, our hypothesis is that in the presence of the EVSE or EV charging timer, customers are much more willing to shift load away from the peak and off-peak periods than they would be to shift other types of residential loads. Regardless of the explanation, based on the load shapes, we do not expect the elasticity estimates here to be comparable to those in other TOU experiments.

The estimated elasticities for the peak period and off-peak period are quite a bit higher than the most comparable results from an outside study that we are aware of – those from the California Statewide Pricing Pilot. In that study, daily own-price elasticities for residential customers were generally found to be in the range of negative 0.3-0.5.[23] The large own-price elasticity estimates may be due to the EVSE or EV charging timers, which make it easier for the customer to respond to the pricing signal and charge during the lowest price period. The own-price elasticity estimates for the super off-peak period are similar to those found in the Statewide Pricing Pilot.

Not all of the cross-price elasticities are positive, which is unexpected. We would expect that electricity usage between any two periods to be substitutes, however Table 5-7 suggests that electricity usage between the peak and off-peak hours are partially complementary because ϵ_{p-op} is negative across all price schedules and ϵ_{op-p} is negative for EPEV-L. This implies that all else being equal, an increase in the off-peak period price causes a decrease in the usage of electricity in the peak period. This seems unlikely to reflect actual behavior. This weakness in the results is due to our attempt to estimate substitution patterns between the peak and off-peak periods, both of which contain quite low levels of charging. The model requires a certain amount of meaningful variation in usage across the rate periods in order to be able to measure the implicit trade-offs that participants make when charging at different times. As we can see in Tables 5-3 and 5-4, the instantaneous level of charging at any given time is typically only slightly different between the off-peak and peak periods, and on the weekends it is actually slightly higher during the peak period. This suggests that many customers do not differentiate between the peak and off-peak periods in their charging decisions. A simple rule a customer might use to decide when to charge that could lead to this pattern would be "use the timer to charge overnight as much as possible, and then charge at other times as necessary." That could lead to the odd cross-price elasticities below. In that case, we would generally expect that the estimates would be statistically insignificant, and two of the eight unexpected values are, leaving

22 Additional tables of results, including results from different subsets of the data are included in Appendix B.

23 See "Impact Evaluation of the California Statewide Pricing Pilot." Prepared by Charles River Associates, (2005).

six that are not. This is more than we would expect due to chance alone if all the model's assumptions are satisfied, which suggests that some of the model's assumptions may be inaccurate. Currently there is no simple way to determine which of the model's assumptions lead to this unexpected finding. The model employs numerous simplifications of reality in order to produce a regression function with parameters that can be estimated based on the available data. This type of finding is to be expected in a fairly simple model of such a complex phenomenon and it is a well-recognized problem with demand modeling in general.

Our recommendation is to focus on the results for the super off peak period as compared to the other two periods and wait for additional data collection and analysis to determine whether reliable conclusions can be drawn about substitution between the peak and off-peak periods.

Table 5-7: Elasticity Results

Type of Price Elasticity	Elasticity	Rates					
		Summer			Winter		
		EPEV-L	EPEV-M	EPEV-H	EPEV-L	EPEV-M	EPEV-H
Own	ϵ_{p-p}	-0.81	-1.18	-1.67	-0.72	-1.00	-1.35
	ϵ_{op-op}	-0.82	-1.18	-1.20	-0.81	-1.04	-1.06
	$\epsilon_{sop-sop}$	-0.24	-0.28	-0.29	-0.23	-0.27	-0.28
Cross	ϵ_{p-op}	-0.13	-0.28	-0.41	-0.12	-0.22	-0.31
	ϵ_{op-p}	-0.56	0.81	0.60	-0.35	1.26	0.71
	ϵ_{p-sop}	0.94	1.42	2.11	0.83	1.22	1.74
	ϵ_{sop-p}	0.10	0.12	0.13	0.08	0.11	0.12
	ϵ_{op-sop}	0.90	1.36	1.43	0.87	1.18	1.24
	ϵ_{sop-op}	0.14	0.17	0.16	0.15	0.17	0.15

= statistically insignificant at 5% level

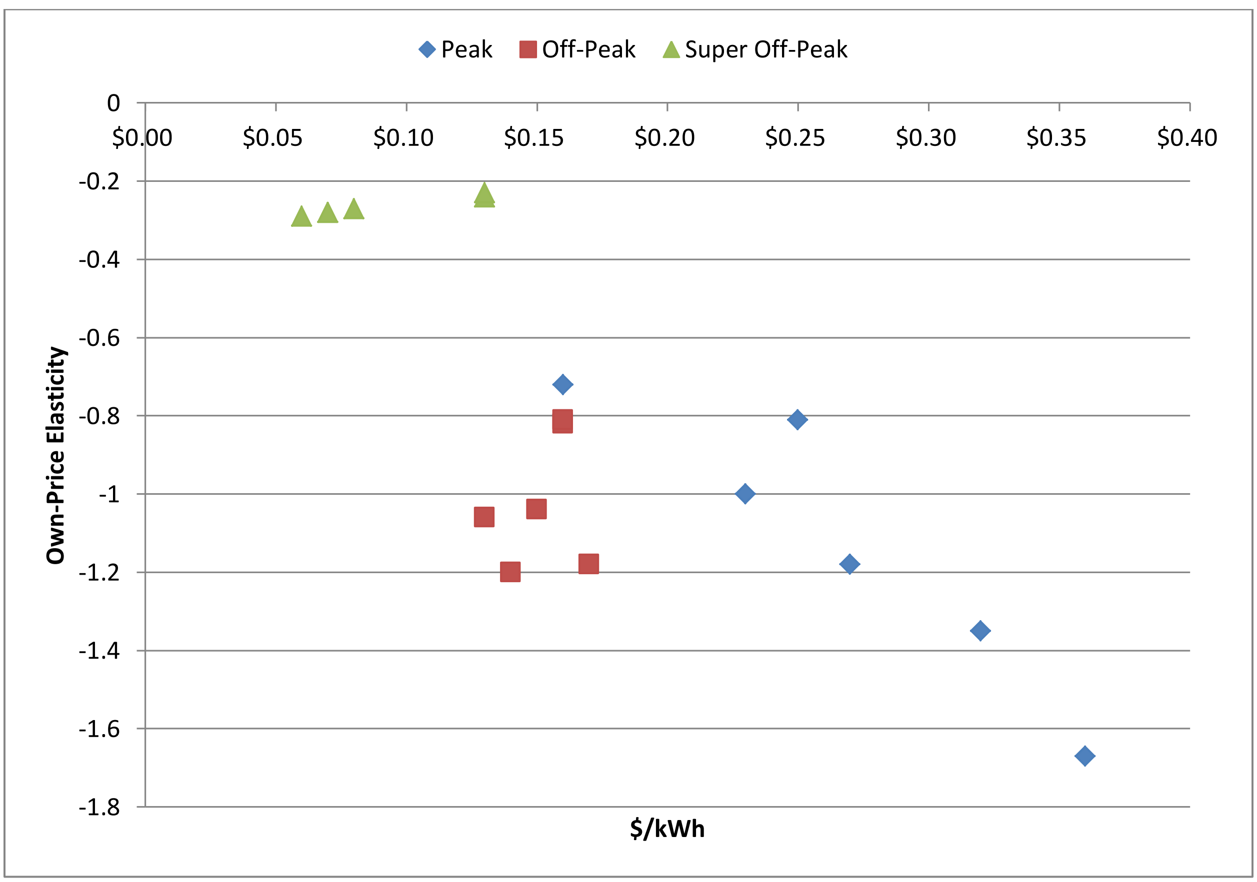
A few important patterns show up in Table 5-7. First, all of the own-price elasticities increase in absolute value as the price ratio between peak and off-peak or between peak and super off-peak prices increases across the price schedules. This indicates that as prices become more extreme in favoring certain time periods, households are more willing to respond by changing charging decisions. This is sensible; there may be a certain fixed cost to customers of responding at all and this cost might vary across customers. Faced with a weak price ratio, some customers might not find it worth it to respond at all, while others would respond weakly. As the price ratio increased, more and more customers might find it worthwhile to respond. This would lead to the pattern of estimated own-price elasticities shown in Table 5-7.

Second, and similar to the first pattern, own-price elasticities are greater in absolute value for the higher prices in each rate schedule. The peak own-price elasticity is greater than the off-peak own-price elasticity which, in turn, is greater than the super off-peak own price elasticity. This pattern holds for summer and winter across all three rates. A similar explanation as for the first pattern may hold. In the super off-peak period, prices may be so low that small changes in price may not be worth responding to at all for some customers. As the price increases into the off-peak and peak periods, more and more customers will find it worthwhile to respond.

These two patterns described in the paragraphs above are shown in Figure 5-2, which graphs the elasticity estimates from Table 5-7 against the price for each estimate. The main notable feature of the graph is that across the time periods we see that customers are more responsive when the price is higher. Down in the low prices of the super off-peak period, customers don't respond much to price changes– probably because the prices are so low that it's not worth paying too much attention. Up in the peak period price range, customers respond a lot to price changes. As stated earlier, price elasticities are usually considered in terms of the magnitude of their absolute value, with large absolute values indicating more elastic demand. Specifically, a price elasticity of absolute value greater than 1 is usually considered highly elastic.

Importantly, during the peak period alone we also see that as the price gets higher, customers continue to get more and more price responsive. Customers facing the highest prices are also the most responsive (meaning customers on EPEV-H during the summer). This says that a preliminary result is that customers respond to prices and the biggest price response occurs towards the upper end of the prices currently being tested.

Figure 5-2: Elasticity Results Versus Prices During Each Period



Preliminary Results

Finally, and again, similarly, the cross-price elasticities tend to be higher for the high price periods and lower for the low price periods. This pattern holds both across periods and across rate schedules (with the already mentioned exception of ϵ_{op-p} and ϵ_{p-op}). For example, the elasticity of on-peak charging with respect to the price of super off-peak charging (ϵ_{p-sop}) is much greater than the elasticity of super off-peak charging with respect to the price of on-peak charging (ϵ_{sop-p}). This pattern, which also holds between off-peak and super off-peak periods, is probably partially due to the fact that so much charging takes place during the super off-peak period for all rates despite price differentials across rates. Fairly large changes in the peak price, for example, have led to little change in the pattern of super off-peak charging across rates. It is less clear why the low rates of charging during the peak and off-peak periods have led to higher cross-price elasticities for those quantities.

To assess how well the model fits the data, we use the model to predict usage shares for each period based on the TOU price schedules. The model does a good job of predicting the average monthly share of usage for each of the rate groups. Table 5-8 shows the predicted versus actual shares for each of the TOU periods. The actual shares never deviate by more than 1% from the predicted share. This indicates that the model fits the data well on average at these prices.

Table 5-8: Predicted Versus Actual Usage Shares

Rates	Shares (%)					
	Predicted			Actual		
	EPEV-L	EPEV-M	EPEV-H	EPEV-L	EPEV-M	EPEV-H
EPEV-L	6	10	84	6	10	84
EPEV-M	8	13	78	9	13	78
EPEV-H	7	11	82	7	11	82

Note: Not all shares total 100% due to rounding.

The R^2 value is an additional way to consider how well the model fits the data. The model consists of two equations being fit to the data. The equations describe the share of usage in the peak period and the super off-peak period. The off-peak usage is fully determined by the other two equations because the total shares of usage must sum to one. The R^2 value of the super off-peak peak period equation is 94%, indicating a very close fit of the model to the data. The R^2 value of the peak period equation is 33%, indicating a much looser fit, with more unexplained variation. Essentially, the model can predict super off-peak period usage well because such a large fraction of charging occurs then. Peak period charging, on the other hand, is much rarer, more idiosyncratic and difficult to predict accurately. As more data is collected, the model's ability to fit peak period charging may increase, which would lead to a higher R^2 value.

Having estimated this model, a useful feature is that it allows us to predict what usage behavior would look like under alternative price schedules for the same population. The model we used provides us with estimated demand functions. We can input different hypothetical prices into the estimated demand functions to see how the share distributions vary. Table 5-9 shows the predicted shares of usage for various TOU rates. For example, it allows us to compare the impact of an extreme rate with a price ratio of 1:2:13 to the EPEV-H summer rate which has a ratio of 1:2.3:5.7

Table 5-9: Shares of Usage for Different Pricing

Ratio of Prices (sop:op:p)	Shares (%)		
	Peak	Off-peak	Super Off-peak
1:2.3:5.7	5	10	85
1:3:8	3	7	90
1:2:13	0	6	94

The results indicate that customers are responding to the price incentives of charging during super off-peak hours. Table 5-10 shows the estimated usage values in kWh for each rate period under the alternative scenarios analyzed in Table 5-10. Under the most extreme rate scenario, with a peak to super off-peak ratio of 1:13, the peak usage falls to less than 1% of total usage.

Table 5-10: Total Daily Usage by Period for Different Pricing (kWh)

Price Ratio	Peak	Off-peak	Super Off-peak
1:2.3:5.7	0.50	0.88	7.76
1:3:8	0.23	0.66	8.25
1:2:13	0.00	0.55	8.59

SDG&E's standard residential rate is an increasing block rate, which means that ideally we would be able to predict usage under that schedule. Block rates provide different incentives than TOU rates, with a focus on the distribution of usage over the month rather than the distribution of usage during the day. Customers within this experiment were not subject to increasing block rates for their charging, so there is no way to use the data in this experiment to develop a model that accounts for behavior under TOU rates and an increasing block rate.

Overall, the results of this section show that customers in the SDG&E Rate Experiment have usage behavior that can be reasonably well modeled using a standard economic demand model. However, it is important to note that peak period charging in particular has much variation in it that is unexplained by the model. This modeling exercise may become more informative over the second year of the pilot if customers start to deviate more from super off-peak charging.

6 Conclusions

This report is a summary of preliminary results for the first year for the SDG&E EV Rate Experiment. Conclusions from this report may change as additional data is collected and analyzed. The final report for this experiment is expected in 2013.

The key findings of this report are that:

- The majority of charging takes place during the super off-peak period, which is likely driven by the use of EVSE and EV charging timers;
- This pattern constitutes strong evidence of the impact of the TOU rate on charging behavior;
- There is evidence that customer behavior is changing over time; and
- Charging behavior does not significantly vary across different demographic groups of income, age or education.

A significant amount of evidence suggests that charging behavior is driven by the use of EVSE or EV charging timers. Sixty-three percent of all charging events begin between the hours of 12 AM to 1 AM and 80% of total EV charging usage occurs during the super off-peak period. This suggests that customers are setting their timers to start charging at the beginning of the super off-peak period to take advantage of the lowest electricity rate.

Aside from the strong tendency towards super off-peak charging, there is further evidence that the TOU rates are impacting customer EV charging behaviors. Looking across the different TOU rate groups, customers on the flattest TOU rates charge less during the super off-peak hours and more during the peak hours than the other groups of customers who face steeper price increases in the peak period. Examining usage within customers, customers are doing the majority of EV charging during the lowest priced periods and the estimated own-price elasticities are relatively large.

Customer EV charging behavior appears to be changing over time. Over the course of the experiment, customers on the flattest TOU rate have seen the largest decline in the super off-peak period's share of total usage. Conversely, customers on the steepest TOU rate have seen virtually no decline in the super off-peak period's share of total usage. This suggests that customers may be learning more about their rates over time and adjusting their behavior accordingly. However, these differences are currently driven by a small number of customers, so it will be important to see whether they hold up over time.

The results of this analysis must be viewed in the proper context. All of the information used in the analysis comes from customers who are early adopters of new technology. For this reason we cannot assume that the behavior observed in them will necessarily be demonstrated by a larger population after widespread EV technology adoption. However, the analysis contained in this report is a necessary starting point and provides valuable information about general trends in the participant population.

Over the course of the next year of the study it will be useful to repeat the same analyses to determine whether customers diverge in their charging behavior according to the price signals they face.

Appendix A. Model Development

A.1. Model

In order to estimate the effects of TOU pricing with the available data we need to model electricity demand within a structural framework. For this reason, we model the household as a firm that produces many outputs. We focus on one output in particular: the usage of an electric vehicle. Using this framework, the inputs of production become the electricity used in each of the pricing periods: peak, off-peak and super off-peak, with all other inputs, and their corresponding prices, being held constant. We can then estimate parameters of the cost function, which is analytically derived from the hypothetical production function, by using load data and the price variation across different customers. The estimated parameters of the cost function provide us with the input demand functions, from which we can then derive elasticities and calculate the impacts of the TOU rates.

We model the energy usage of the electric vehicle supply equipment (denoted EVSE) with a generalized Leontief (GL) production function. Using this model we can derive a demand system for EVSE energy consumption that represents each pricing period's demand. The model we use is essentially a special case of the model presented in Aigner, Newman and Tishler (1994), who examine non-residential TOU rates in Israel. We use the case of the model with three period pricing: peak, off-peak and super off-peak.

The GL production function was introduced by Diewert (1971)[24] to obtain input demand equations that are linear in technological parameters for the purposes of facilitating econometric estimation. We choose the GL function because it is sufficiently sophisticated to take advantage of the experimental design, and simple enough to satisfy global concavity for the sake of estimation (and therefore ensuring unique solutions to the estimation procedure). More complex models, like the CES-GBC, include more parameters and do not necessarily satisfy global concavity.[25] Global concavity is important for optimization problems, because it implies a unique solution to a problem. In this setting, concavity means that there is a set of parameters for our production function that minimize the aggregate differences between the actual and predicted values.

Faruqui and Malko (1983)[26] claim that the GL specification offers a degree of flexibility, in that it imposes few restrictions on the substitution possibilities. This feature allows us to take full advantage of the experimental design (having three distinct TOU rates for each of the three time periods) and estimate own-price elasticities and cross-price elasticities between all of the time periods. Other

[24] Diewert, W. E. "An Application of the Shephard Duality Theorem: A Generalized Leontief Production Function." Journal of Political Economy. (1971).

[25] Tishler, A. and S. Lipovetsky, "The Flexible CES-GBC Family of Cost Functions: Derivation and Application", Review of Economics and Statistics. (1997).

[26] Faruqui, A and J. R. Malko. 1983. "The Residential Demand for Electricity by Time-of-Use: A Survey of Twelve Experiments with Peak Load Pricing." Energy Vol. 8. (1983).

models, like the translog model used in Chung and Aigner (1981)[27] are incapable of testing the hypothesis of zero substitutability between periods.[28]

The GL model also tends to perform well with relatively large price variations. In a similar experiment looking at commercial TOU rates, Woo (1985) highlights the benefits of the GL specification when examining TOU price variations ranging from 8:1 to 2:1 in peak to off-peak ratios. Woo found that the GL model produced a better fit, and more intuitive elasticity results, than the translog model, which produced counter-intuitive positive own-price elasticities for some of the pricing periods.

The model will use 15-minute interval data that measures the usage of the EVSE. The 15-minute data is aggregated such that dependent variables are the monthly average shares of on-peak, off-peak, and super off-peak, weekday electricity consumption. Therefore, the shares represent each pricing period's fraction of the total monthly weekday energy consumed by the EVSE. Share models are used as a way of normalizing EVSE loads so that relative usage within a given pricing period can be easily compared across customers in a panel model.

The foundation of the model is a three input generalized Leontief production function of the form:

$$y = \sum_{i=1}^{3} \sum_{j=1}^{3} {}_{ij}\left(x_i x_j\right)^{1/2} \tag{A-1a}$$

where y is output, x_i for $i = 1,2,3$ are inputs (which in this is case electricity used during each price period), and α_{ij} for $i, j = 1,2,3$ are unknown parameters. This function describes how a household in the study produces value from its charging consumption at different times of day.

Given equation (A-1a), we assume that a customer can then find the minimum cost usage allocation to produce a given feasible amount of value for any price schedule: p_i for $i = 1,2,3$. Solving this cost minimization problem,

$$\min \sum_{i=1}^{3} x_i p_i \tag{A-1b}$$

subject to the constraint

$$y = \sum_{i=1}^{3} \sum_{j=1}^{3} {}_{ij}\left(x_i x_j\right)^{1/2} \tag{A-1c}$$

[27] Chung, C. and D. J. Aigner. "Industrial and commercial demand for electricity by time-of-day: A California case study," The Energy Journal, (1981).

[28] Woo, C. "Demand for Electricity of Small Nonresidential Customers under Time-Of-Use (TOU) Pricing." The Energy Journal. (1985).

results in the cost function of Aigner, Newman and Tishler (1994):

$$C = y\sum_{i=1}^{3}\sum_{j=1}^{3} {}_{ij}\left(p_i p_j\right)^{1/2} \tag{A-2}$$

With input prices p_i for $i = 1,2,3$ and parameters β_{ij} for $i, j = 1,2,3$ which are unknown parameters to be estimated.

At the point where costs are minimized, the rate of change of the cost as price changes is equal to the level of demand of that commodity. Therefore, taking the partial derivatives of the cost function with respect to input price, we get the demand for each input i:

$$\frac{\partial C}{\partial p_i} = x_i = y\sum_{j=1}^{3} {}_{ij}\left(\frac{p_j}{p_i}\right)^{1/2} \qquad i = 1,2,3 \tag{A-3}$$

The resulting share equations are:

$$m_i = \frac{x_i p_i}{\sum_k x_k p_k} = \frac{\sum_j {}_{ij}\left(p_i p_j\right)^{1/2}}{\sum_k \sum_j {}_{kj}\left(p_k p_j\right)^{1/2}} \qquad i = 1,2,3 \tag{A-4}$$

where m_i is the share of the ith input in total electricity expenditure and x_i is the electricity use during the period when p_i is in effect. Note that in the denominator of (A-4), the *k* and *j* indices each go from 1 to 3. Dividing the top and the bottom of equation (A-4) by p_i demonstrates that the share equations are dependent only on the price ratios p_j/p_i , for $j = 1,2,3$. Taking the derivative of the demand (A-3) with respect to the prices, the own-price and cross-price elasticities then respectively become:

$$\epsilon_{ii} = \frac{\partial \ln(x_i)}{\partial \ln(p_i)} = \left(\frac{\partial x_i}{\partial p_i} * \frac{p_i}{x_i}\right) = \frac{1}{2}\left[\frac{{}_{ii}}{\sum_j {}_{ij} p_j^{1/2} p_i^{-1/2}} - 1\right] \qquad i = 1,2,3 \tag{A-5a}$$

and:

$$\epsilon_{ij} = \frac{\partial \ln(x_i)}{\partial \ln(p_j)} = \left(\frac{\partial x_i}{\partial p_j} * \frac{p_j}{x_i}\right) = \frac{1}{2}\frac{{}_{ij} p_j^{1/2} p_i^{-1/2}}{\sum_j {}_{ij} p_j^{1/2} p_i^{-1/2}} \qquad i \neq j \tag{A-5b}$$

In the denominator of (A-5a) and (A-5b), the *j* index goes from 1 to 3. Weather may impact electricity usage; therefore, we define:

$${}_{ij} = {}^{0}_{ij} + W\ {}^{1}_{ij} \tag{A-6}$$

where W is the average monthly weekday measurement of cooling degree hours (CDH) taken at 2 PM PST.[29] Finally, equations (A-4) are homogenous of degree zero in the β_{ij}'s; therefore we impose the following restrictions to ensure identifiability:

$$\sum_i \sum_j \; {}^{0}_{\mathrm{ij}} = 1/2 \qquad \text{(A-7a)}$$

and:

$$\sum_i \sum_j \; {}^{1}_{\mathrm{ij}} = 0 \qquad \text{(A-7b)}$$

where the *i* and *j* indices each go from 1 to 3.

A.2. Estimation

We specify classical additive disturbances (u) for each of the share equations (A-4) which result in equations (A-8) below. Aggregated 15-minute data is used to estimate the monthly share equations (A-4) subject to the constraints (A-6), (A-7a) and (A-7b). Since the shares must add up to one, the equation for the super off peak period is deleted ($m_3 = 1 - m_1 - m_2$). The remaining share equations from (A-5), subject to the constraints (A-6), (A-7a) and (A-7b), are then estimated using nonlinear seemingly unrelated regressions (SUR).

This results in the system:

$$m_i = \frac{\sum_j \; {}_{\mathrm{ij}}\left(\mathrm{p_i p_j}\right)^{1/2}}{\sum_k \; \sum_j \; {}_{\mathrm{kj}}\left(\mathrm{p_k p_j}\right)^{1/2}} + u_i \qquad i = 1,2 \qquad \text{(A-8)}$$

where:

$$ {}_{\mathrm{ij}} = \; {}^{0}_{\mathrm{ij}} + \mathrm{W} \; {}^{1}_{\mathrm{ij}} \text{ for i, j} = 1,2,3 \qquad \text{(A-9a)}$$

$$ {}^{1}_{33} = \sum_i \sum_j \; {}^{1}_{\mathrm{ij}} \, for\ i,j \neq 3,3 \qquad \text{(A-9b)}$$

and:

$$ {}^{0}_{33} = \frac{1}{2} - \sum_i \sum_j \; {}^{0}_{\mathrm{ij}} \, for\ i,j \neq 3,3 \qquad \text{(A-9c)}$$

The estimation of the SUR model will be done in STATA, using the *nlsur* function, which fits a system of nonlinear equations by feasible generalized nonlinear least squares (FGNLS). FGNLS is used because the error variance matrix is unknown, but can be estimated in the first stage of the estimation (see (A-11) below).

[29] The actual implementation of the model in this paper did not include weather because the model would not converge on a solution when weather was included.

The NLSUR model takes into account the notion that the errors between two nonlinear regression equations can be correlated. If these errors are correlated, the SUR model can improve the efficiency of the estimation. In the case of the share equations we have derived above, this relationship should be clear, as the total shares: peak, off-peak and super off-peak, must add up to one. Therefore, overestimating one share should result in an underestimation of one or more of the other shares.

Using matrix notation, the FGNLS estimator for N observations is $\hat{\beta}$, such that:

$$\hat{\beta} \equiv argmin_{\beta} \sum_{j=1}^{N} \big(m_j - g(x_j, \beta)\big)\delta'\big(m_j - g(x_j, \beta)\big)' \tag{A-10}$$

Where $g(x_j, \beta)$ is the vector of functions $g(x_{ji}, \beta) = m_{ji} + u_{ji}$ for $i = 1{,}2$ given in (A-6) for the jth observation.

The FGNLS is essentially a two stage process. In the first step we run the NLS regression assuming $\delta = I\ (identity\ matrix)$ in (A-10). This will give us a consistent estimate of β, $\hat{\beta}_{NLS}$ which is then used to estimate δ as follows.

$$\hat{\delta} = \sum_{i=1}^{N} \frac{1}{N} \hat{u_i}' \ \hat{u_i} \tag{A-11}$$

where:

$$\hat{u_i} = m - g(x_i, \hat{\beta}_{NLS}) \tag{A-12}$$

$\hat{\delta}$ is then plugged into (A-10) for δ which gives us a new estimate of β, $\hat{\beta}_{FGNLS}$.

Appendix B. Results from Different Subsets of Data

The following tables show the results of the model when it is estimated for different subsets of the data. The first subset contains all data later than June 1, 2011. This is when enrollment leveled off. The results from this subset of data are presented in Tables B-1 and B-2. The results of this model are very similar to those that used the entire dataset.

Next, Tables B-3 and B-4 present the results of the model using only summer data. Here we see that every elasticity is closer to zero compared to the complete data set and Table B-1. This is expected, since the price differentials are larger in the summer while usage patterns are similar. Therefore, every change in usage across periods will be accompanied by a relatively larger percent change in price, and thus lead to a smaller elasticity. This notion is reinforced by Tables B-5 and B-6, which present the results of the model using only the winter data. Here we see that all of the elasticities are further from zero relative to the complete data set and Table B-2.

As was the case in the primary model, estimation of ϵ_{op-p} continues to be problematic in these examples. The elasticity calculations are a function of the β parameters, and sometimes the denominator of the calculation can be quite close to zero due to combinations of parameters that would otherwise seem reasonable. We will investigate this issue further if it continues to arise.

Table B-1: SUR Model Results Monthly Data (All Data Later than June 1, 2011)

Parameter	Coefficient	Std. Err.	z	P>|z|	95% Confidence Interval	
β_{11}	-0.014	0.001	-10.57	0	-0.016	-0.011
β_{12}	-0.008	0.003	-3.02	0.003	-0.013	-0.003
β_{13}	0.059	0.004	15.64	0	0.052	0.066
β_{22}	-0.034	0.007	-5.13	0	-0.047	-0.021
β_{23}	0.109	0.008	13.87	0	0.093	0.124
β_{33}	0.228	0.013	17.73	0	0.203	0.253

Table B-2: Elasticity Results (All Data Later than June 1, 2011)

Type of Price Elasticity	Elasticity	Rates					
		Summer			Winter		
		EPEV-L	EPEV-M	EPEV-H	EPEV-L	EPEV-M	EPEV-H
Own	ϵ_{p-p}	-0.81	-1.18	-1.69	-0.72	-1.01	-1.36
	ϵ_{op-op}	-0.80	-1.14	-1.16	-0.79	-1.01	-1.03
	$\epsilon_{sop-sop}$	-0.23	-0.28	-0.29	-0.22	-0.26	-0.28
Cross	ϵ_{p-op}	-0.13	-0.29	-0.42	-0.12	-0.23	-0.32
	$\epsilon_{op-p}{}^{*}$	-0.45*	1.38*	0.79*	-0.29*	3.66*	1.01*
	ϵ_{p-sop}	0.94	1.43	2.14	0.83	1.23	1.75
	ϵ_{sop-p}	0.10	0.12	0.13	0.08	0.11	0.12
	ϵ_{op-sop}	0.89	1.33	1.40	0.86	1.15	1.22
	ϵ_{sop-op}	0.14	0.16	0.15	0.14	0.16	0.15

*Statistically insignificant at the 5% level.

Table B-3: SUR Model Results Monthly Data (Summer Data Only)

Parameter	Coefficient	Std. Err.	z	P>|z|	95% Confidence Interval	
β_{11}	-0.012	0.002	-6.56	0	-0.016	-0.008
β_{12}	-0.008	0.003	-2.42	0.015	-0.015	-0.002
β_{13}	0.057	0.005	10.7	0	0.046	0.067
β_{22}	-0.026	0.008	-3.37	0.001	-0.041	-0.011
β_{23}	0.097	0.011	9.21	0	0.076	0.117
β_{33}	0.247	0.019	12.92	0	0.210	0.285

Table B-4: Elasticity Results (Summer Data Only)

Type of Price Elasticity	Elasticity	Rates		
		Summer		
		EPEV-L	EPEV-M	EPEV-H
Own	ϵ_{p-p}	-0.77	-1.07	-1.43
	ϵ_{op-op}	-0.74	-0.99	-1.01
	$\epsilon_{sop-sop}$	-0.21	-0.26	-0.27
Cross	ϵ_{p-op}	-0.14	-0.29	-0.40
	$\epsilon_{op-p}{}^{*}$	-0.31*	-2.08*	3.83*
	ϵ_{p-sop}	0.91	1.32	1.85
	ϵ_{sop-p}	0.09	0.11	0.13
	ϵ_{op-sop}	0.84	1.18	1.26
	ϵ_{sop-op}	0.12	0.15	0.14

*Statistically insignificant at the 5% level.

Table B-5: SUR Model Results Monthly Data (Winter Data Only)

Parameter	Coefficient	Std. Err.	z	P>|z|	95% Confidence Interval	
β_{11}	-0.017	0.002	-9.1	0	-0.021	-0.013
β_{12}	-0.010	0.004	-2.28	0.023	-0.018	-0.001
β_{13}	0.067	0.006	10.88	0	0.055	0.079
β_{22}	-0.037	0.013	-2.8	0.005	-0.063	-0.011
β_{23}	0.120	0.014	8.39	0	0.092	0.148
β_{33}	0.200	0.020	10	0	0.161	0.239

Table B-6: Elasticity Results (All Winter Data Only)

Type of Price Elasticity	Elasticity	Rates		
		Winter		
		EPEV-L	EPEV-M	EPEV-H
Own	ϵ_{p-p}	-0.75	-1.14	-1.69
	ϵ_{op-op}	-0.80	-1.03	-1.06
	$\epsilon_{sop-sop}$	-0.25	-0.29	-0.31
Cross	ϵ_{p-op}	-0.14	-0.30	-0.47
	ϵ_{op-p}*	-0.32*	4.05*	1.09*
	ϵ_{p-sop}	0.89	1.42	2.29
	ϵ_{sop-p}	0.09	0.12	0.14
	ϵ_{op-sop}	0.88	1.21	1.29
	ϵ_{sop-op}	0.16	0.17	0.16

*Statistically insignificant at the 5% level.