Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study

Submitted to San Diego Gas & Electric

Submitted By Nexant, Inc.

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Table of Contents

1 Executive Summary

This report documents results from San Diego Gas & Electric Company's (SDG&E's) multi-year plug-in electric vehicle (EV)[1] Pricing and Technology Study (Study), incorporating a temporary experimental EV rate approved by the California Public Utilities Commission (CPUC).[2] The Study employed a randomized control trial (RCT) experimental research design whereby SDG&E EV customer participants were randomly assigned to one of three EV tariffs, each with different price ratios between on-peak, off-peak and super off-peak rates. The Study was approved by the CPUC to provide an early view of EV customer charging response to time-varying rates for EV charging to help inform state electricity pricing policy.

Customer decisions regarding when they charge their EV at home have major implications regarding distribution system planning and operations as well as system capacity needs. It is important to understand the degree to which pricing and technology influence these decisions before the rate of EV adoption increases in SDG&E's service territory, especially if it is determined that pricing and technology have a strong influence. For example, if EVs are charged at peak times, then each vehicle is roughly equivalent to an additional household's load added to a neighborhood.[3] This could require adding system capacity, as well as near term distribution system upgrades. On the other hand, if EV customers can be encouraged to charge during off-peak times when system capacity is plentiful then enhancements to system capacity can be avoided or deferred.

Overview of Experiment

The San Diego region was one of a number of regional sites selected for launching the EV Project, funded by the U.S. Department of Energy (DOE) as the nation's largest deployment of EV charging infrastructure. The selection of the San Diego region for the EV Project was in part due to Nissan's announcement to target the region for the 2011 launch of the Nissan LEAF deployment in significant volumes. Together, these unique market conditions created an opportunity for SDG&E to propose and design a study with CPUC approval to examine EV customer time-of-use charging behavior.

The Study tested three experimental 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 through the EV Project qualifying process were randomly assigned to one of the three TOU rates for the duration of the Study. The rates apply only to load or usage from the electric vehicle supply equipment (charging unit) and not to the customer's entire house load, and were separately metered and billed. The Study only examines charging behavior at home; it does not look at public or other non-home charging facilities.

Each rate consists of different prices for charging during each of the TOU periods. The on-peak period runs from noon to 8 PM, the off-peak period runs from 8 PM to 12 AM and 5 AM to noon, and the super

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

[2] SDG&E EV TOU Pricing and Technology Study, Advice Letter 2157-E (U 902-E), filed March 26, 2010 and approved by the CPUC, June 24, 2010, Resolution E-4334.

[3] Typical peak EV charging load for a given household in this study is 2.5-3 kW. Households in SDG&E's territory typically have peak summer loads of 1-2 kW. Typical summer loads vary depending on many factors, such as the presence of central air-conditioning.

off-peak period runs from 12 AM to 5 AM. These TOU periods do not vary by day of week and make no exceptions for holidays, or summer and winter seasons. The three rates were designed to test low, medium and high price ratios between the on-peak and super off-peak TOU periods. In addition, the three rates have different price ratios between on-peak and off-peak prices and between the summer and winter seasons. The low rate (EPEV-L) has an on-peak to super-off peak price ratio of roughly 2:1, the medium rate (EPEV-M) has a ratio of roughly 4:1 and the high rate (EPEV-H) ratio is roughly 6:1. Approximately 430 participants were assigned to one of the three experimental rates.

In this experiment, the SDG&E customer participants all had the following characteristics:

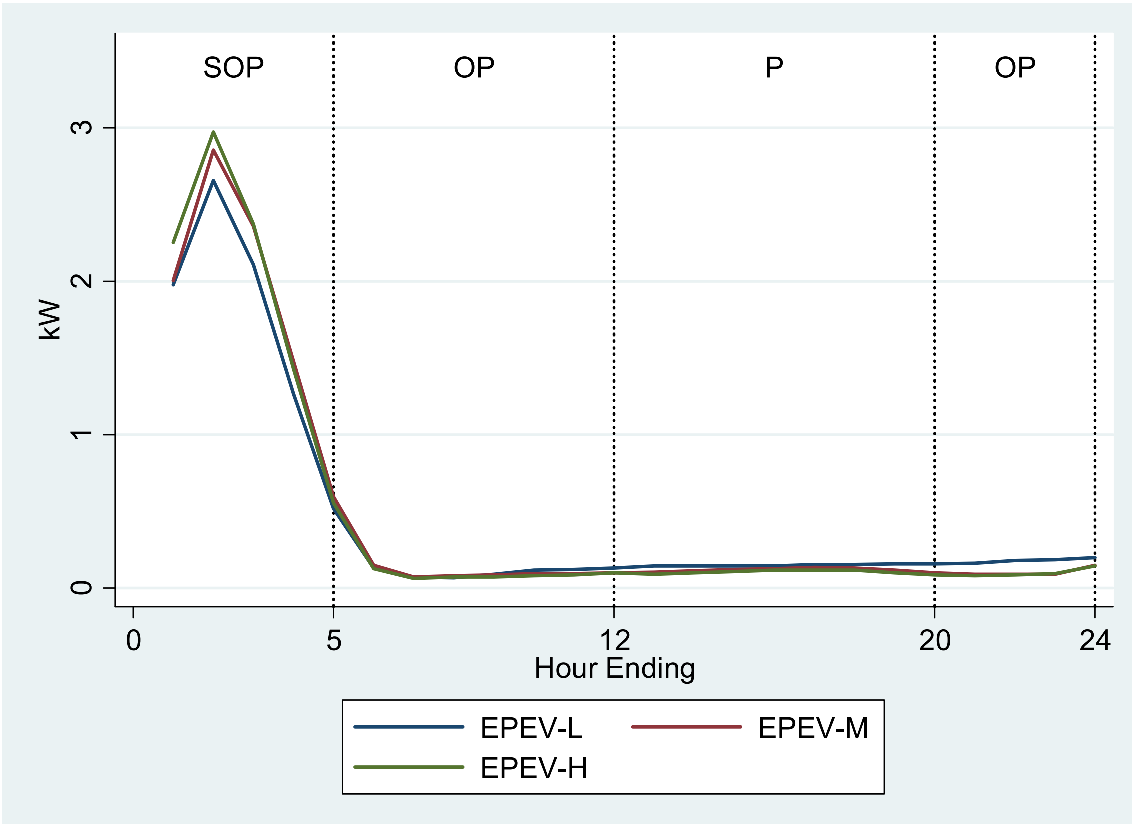
- qualified to participate in the nationwide EV Project;
- owned or leased the all-electric Nissan LEAF;
- were on one of three randomly assigned experimental time-of-use (TOU) EV rates;
- had a Level 2 (240 volt) home charging unit (provided by the EV Project);
- had technology available to them through the LEAF or charging unit to set charging times; and
- all EV charging loads were separately metered (and billed) on a dedicated 40 amp home circuit.

The key findings of this Study are the product of a two-year effort to observe and describe when EV charging takes place, to estimate the effect of the TOU price signal on EV charging and to assess the degree to which EV charging behavior changes or persists over time.

Key Finding 1: Participant EV Charging Takes Place Mostly During the Super Off-peak Period Using Charging Timers

Customers participating in the Study, who are subject to TOU prices for their EV charging, begin the vast majority of their EV charging events during the super off-peak period, specifically between 12 AM and 2 AM. Using the shares of total electricity consumption during each period, EPEV-H and EPEV-M customers had the highest percent of total charging done during the super off-peak period (85% and 83%, respectively), while EPEV-L customers had 78% of all charging done during the super off-peak period (78%). This charging pattern was facilitated by using the charging time setting technology available standard with the Nissan LEAF and charging unit. Figure 1-1 shows the charging behavior of customers on each of the three experimental tariffs.

Figure 1-1: Average Daily EV Load Shapes for All Customers on Experimental Rates (Weekdays and Weekends Combined: Charging Days Only)



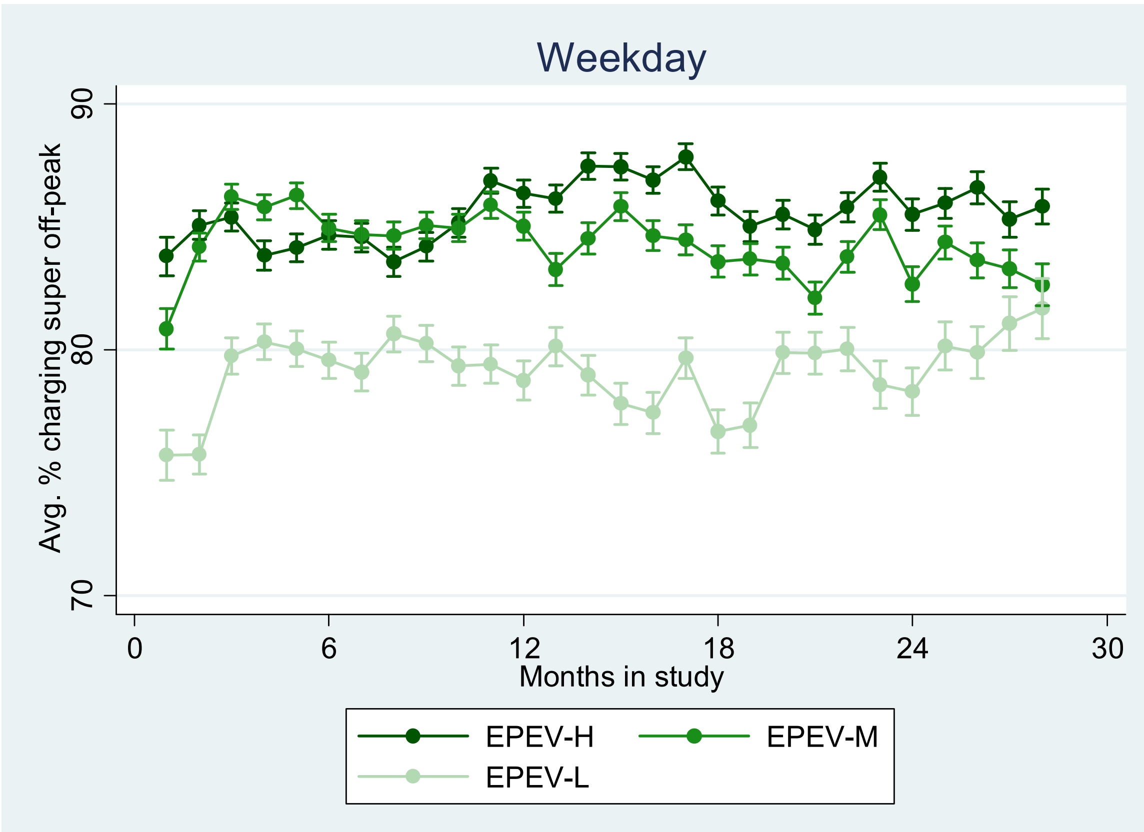
Other conclusions about the timing of EV charging include the following:

- Participant EV charging frequency is greater on weekdays than on weekends;
- Participant EV charging events lasts about three hours on average;
- Participant EV charging patterns do not vary by season;
- The majority of participants do not charge their EVs every day. On days that participants do charge their EVs, charging events generally occur only once per day;
- The majority of participants appear to consistently use timers to control the time of day when EV charging occurs; and
- Participants with Photovoltaic (PV) systems have similar charging patterns as non-PV participants, when compared across all rates. However, participants with PV are less price responsive than non-PV participants.

Key Finding 2: Participant EV Charging Exhibit Learning Behavior

During the first four months of participation in the Study, customers in the EPEV-L and EPEV-M rate groups increased their share of super off-peak charging and decreased their share of peak period charging, a trend seen for both weekday and weekends. In contrast, EPEV-H customers generally exhibited consistent charging behavior for the entire duration of the Study. Figure 1-2 shows the average weekday charging behavior for each rate as function of the number of months after a customer's first charging session. For EPEV-L and EPEV-M customers, the share of super off-peak charging increases by 1.8-2.9% per month and the share of peak charging decreases by 0-1.3% per month during the learning phase compared to the rest of the Study period. Super off-peak charging shares remain relatively stable after the initial upward trend.

Figure 1-2: Average Super-off Peak Proportion of Daily EV Energy Consumption, by Months on Rate[4]



Key Finding 3: Participant EV Charging Behavior Responds to Price Signals

Formal hypothesis tests show that providing stronger price signals to customers causes them to charge relatively more during super off-peak hours and charge less during the on-peak period on both weekdays and weekends. Pair-wise differences in percentage charging shares between rates are shown in Table 1-1. Compared to the EPEV-L rate with the smallest price ratio, the EPEV-M rate increased the share of weekday charging during the super off-peak period by 4 percentage points and reduced the share of peak period charging by 2 percentage points. The EPEV-H rate had a larger effect, increasing the super off-peak charging share by about 6 percentage points and reducing the peak charging share by 3 percentage points relative to the EPEV-L rate.

4 Bars in the graph represent 95% confidence intervals for each average monthly super off-peak charging share.

Table 1-1: Tests of Pair-wise Differences in Percentage Charging Shares Between Rates

Day Type	Charging Share	EPEVL – EPEVM	EPEVL – EPEVH	EPEVM – EPEVH
Weekday	% Peak	1.80	3.08	1.29
	% Super Off-Peak	-4.16	-6.04	-1.87
Weekend	% Peak	2.33	3.25	0.92
	% Super Off-Peak	-4.06	-6.62	-2.55

= Significant at 1%

= Significant at 5%

= Not Significant at 5%

Key Finding 4: EV Customers Are Most Responsive to Changes in On-Peak and Off-peak Prices

In order to apply findings from this Study to future electric vehicle charging rates or to EV rates in other regions, a structural economic model of charging behavior was used to explicitly capture the trade-offs associated with charging during one period versus another and provide estimates of price elasticities for EV charging[5]. The main conclusions from the model are the following:

- Study participants are more responsive to changes in either the peak or off-peak price than to a change in the super off-peak price;
- Study participants who do not own PV systems exhibit similar responses to changes in the price of electricity used for EV charging as to changes in the price of electricity used for other household loads – own-price elasticity estimates are in the range of -0.3 to -0.5;
- Study participants who own a PV system are significantly less responsive to prices than their non-PV counterparts; and
- Simulations of EV charging behavior under TOU rates with other price ratios suggest that a price ratio of 6:1 between peak and super off-peak periods would result in customers using about 90% of their electricity for EV charging during the super off-peak period and that further increases would provide only marginal additional increases in this percentage.

The primary conclusion from the Study is that TOU prices in conjunction with enabling technology, such as the on-board LEAF charging timer or the timer in the charging unit, results in the vast majority of EV customers charging overnight and in the early morning rather than during on-peak times. A large body of evidence suggests that the simple enabling technology of charging timers make it easy and convenient to charge overnight so that a strong tendency for overnight charging is induced by a small rate differential.

This Study provides insight on EV customers' response to time-varying rates for EV charging and constitutes valuable information that can inform rate-setting policy at the CPUC as well as other

[5] Price elasticities are quantitative measures of price responsiveness that denote the percentage change in quantity demanded that would result from a 1% change in the price. Negative values mean as price increases, usage falls. A value of -0.3 means that a 10% price increase would result in a 3% reduction in usage.

jurisdictions. However, the results presented in this report must be viewed in the proper context – all data analyzed here represent the behavior and choices of customers who are early adopters of a new technology – in this case, an all-electric EV. Their behavior can reasonably be expected to be similar to EV customers in the near future, but the extent to which the charging behavior of early adopters represents the behavior of customers who adopt EVs over a longer time horizon is unclear. It is possible that early adopters are demographically different from later adopters, however the relationship between these demographic characteristics and EV charging decisions is not yet known. The analysis contained in this report is an important and necessary starting point and provides heretofore non-existent information about trends and outcomes in the early stage of EV technology adoption.

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2 Introduction

As explained in the Executive Summary, this report documents results from SDG&E's multi-year, plug-in electric vehicle Pricing and Technology Study, incorporating a temporary experimental EV rate approved by the CPUC. The Study employed a randomized control trial experimental research design whereby SDG&E EV customer participants were randomly assigned to one of three temporary TOU tariffs, each with different price ratios between on-peak, off-peak and super off-peak TOU periods. It is important to understand the degree to which pricing and technology influences customer charging decisions before EV adoption increases in SDG&E's service territory. If EVs are charged at peak times, each vehicle is roughly equivalent to an additional household's load added to a neighborhood.[6] This could require adding peaking capacity or making costly investments in the distribution system. On the other hand, if EV customers can be induced to charge during off-peak times, both supply and distribution system capacity investments can be avoided or deferred.

2.1 Study Background

This Study is timely, taking advantage of a unique market condition in the SDG&E service territory: the 2011 launch of the EV Project[7] and initial Nissan LEAF deployment. The San Diego region was one of a number of regional sites selected for launching the EV Project, funded by the U.S. Department of Energy as the nation's largest deployment of EV charging infrastructure. This award was announced August 5, 2009 and provided home electric vehicle supply equipment (EVSE or charging unit), to the first 1,000 customers who purchased or leased a Nissan LEAF EV in the region (please see Appendix A for a summary of Nissan LEAF features, as well as a description of the EV Project). The selection of the San Diego region for the EV Project was in part due to Nissan's announcement to target the region for the 2011 launch of the Nissan LEAF deployment in significant volumes. These unique market conditions created an opportunity for SDG&E to propose a research plan, with approval from the CPUC, to study EV customer time-of-use charging behavior. Insights gained from this Study will inform the CPUC's rate making policies for utility EV customers.

Once the CPUC approved the Study in June 2010, SDG&E worked with the EV Project staff to create a process by which SDG&E customers who qualified for EV Project participation would be offered the opportunity to participate in the SDG&E Study. Customer recruitment into the Study commenced in July 2010 and continued through 2012 (Study data collection took place from early 2011 to October 2013).

The primary goal of the SDG&E Study is to understand the potential impact of EV charging on electric utility infrastructure as well as identify methods to mitigate any negative impacts from integrating these loads into the grid. SDG&E seeks to better understand the degree to which time-variant pricing with

[6] Typical peak EV charging load for a given household in this study is 2.5-3 kW. Households in SDG&E's territory typically have peak summer time loads of 1-2 kW. Typical summer loads vary depending on many factors, such as the presence of central air-conditioning.

[7] In the remainder of this report, we use "Study" to refer to the SDG&E experiment and "EV Project" to refer to the DOE project. The SDG&E Study participants were a subset of customers who participated in the DOE EV Project.

enabling technology can achieve this goal. The Study addresses a number of important questions, including:[8]

- What are the impacts of various TOU rates on EV charging behavior?
- How is EV charging behavior affected by the availability of enabling technology, such as the timer on the charging unit or the timer on-board the LEAF?
- Do EV charging patterns change over time as customers become more familiar with the pricing and resulting charging costs, as well as with the enabling technology?

This Study estimates the impact of EV-specific TOU rates on energy consumption patterns due to charging decisions by EV customers over roughly two and a half years. The Study examines the impact of three experimental EV TOU rates, each of which has three pricing periods: on-peak, off-peak and super off-peak. The rates applied to electricity consumption for EV charging only, and not to the customer's whole house usage. The TOU periods are the same for all three experimental rates: the on-peak period runs from noon to 8 PM, the off-peak period runs from 8 PM to 12 AM and 5 AM to noon and the super off-peak period runs from 12 AM to 5 AM. These TOU periods do not vary by day of week and make no exceptions for holidays, but the prices in each period do differ between summer (May 1 – October 31) and winter months (November 1 – April 30). The three rates were 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 tariffs in the on-peak to off-peak price and between summer and winter seasons. As described below, Study participants were randomly assigned to one of the three experimental EV TOU rates, which eliminated any selection bias that would result from customers choosing a rate that best met their expected driving needs and lifestyle. For comparative purposes, the EV charging patterns from a population of LEAF customers on the standard whole house EV TOU rate were also analyzed.

2.2 Study Participants

Approximately 700 EV Project participants were recruited into the SDG&E Study and 430 of these participants agreed to be randomly assigned to one of the three experimental EV rates (EPEV-L, EPEV-M, and EPEV-H).[9] Recruitment was based on meeting the following criteria: dedicated home parking, access to home electrical panel, own or lease an all-electric Nissan LEAF and agreeing to the installation of a Blink home Level 2 charging unit. The purpose of the screening criteria was to create a homogeneous Study sample to achieve internal validity for the Study. The extent to which this population represents future EV customers is not yet known, however demographic data obtained from EV Project participant surveys indicates that the participant population is representative of market segments targeted by the auto industry for EV sales[10].

[8] These research objectives were filed with the CPUC and more details can be found at http://regarchive.sdge.com/tm2/pdf/2157-E.pdf.

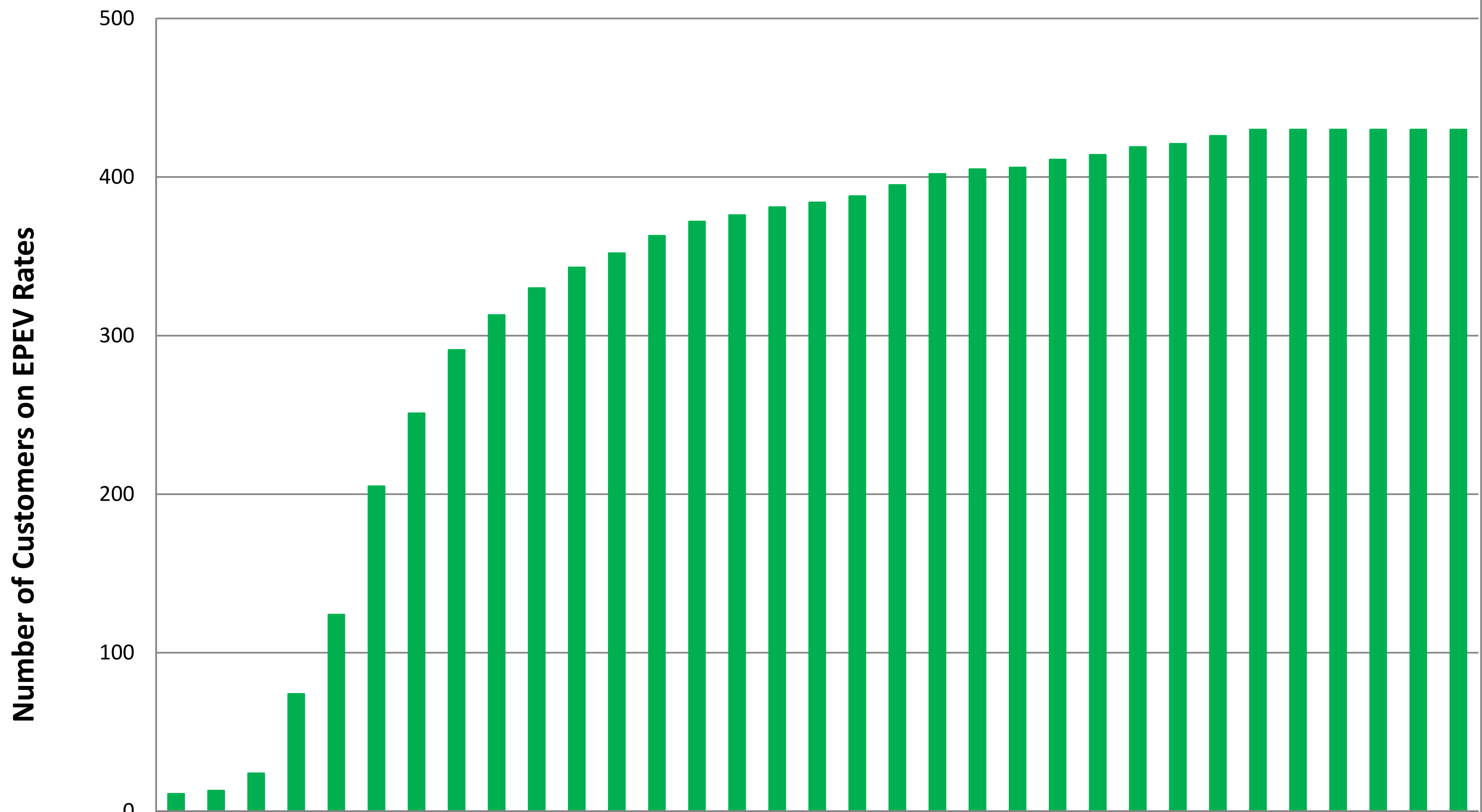
[9] Source: http://avt.inl.gov/pdf/EVProj/LeafsVoltsByRegionMapQ32013.pdf; EV Project participants also include 272 Chevy Volts, and 386 car2go vehicles (car share program), which were not eligible to participate in this Study.

[10] Source: http://www.theevproject.com/cms-assets/documents/128842-80098.devproj.pdf

Not all customers who were part of the EV Project participated in the Study. There were several reasons for this, including problems with configuration of their home, installation costs that exceeded the installation allowance offered by the EV Project or a desire to not be placed on an experimental rate. Three rate options were available for the group of customers who did not choose to be in the Study. First, they could continue to have all their usage, including EV charging, billed on their current rate, which for most participants is the standard tiered residential rate that is undifferentiated by time of day. Second, SDG&E offers an EV rate (EV-TOU-2) that applies to the entire load of a customer's home (a TOU rate applicable to a single home meter). EV-TOU-2 also has three rate periods, but has an on-peak period that runs from noon to 6 PM rather than noon to 8 PM for the separately metered EV loads for the Study participants. The EV-TOU-2 rate periods also do not vary by day of week, but on holidays the EV-TOU-2 on-peak period moves to off-peak status. Finally, SDG&E also offers an electric vehicle TOU rate (EV-TOU) that, like the experimental rates, applies to only the EV load and usage. This rate requires customers to install a separate parallel meter and is rarely chosen.

Figure 2-1 shows how participation increased over time as customers enrolled in the Study, and Figure 2-2 shows the locations of EV Project participants by rate. The number of enrollments for experimental rates shows an initial acceleration, followed by a leveling off in late 2011, with lower numbers of customers entering the Study in late 2012. The map shows the large geographic scale of both the EV Project and the Study. Study participants' homes are located throughout the SDG&E service territory, with the highest number of participants residing in Carmel Valley, a community in the northern part of the city of San Diego. There do not appear to be any patterns in the location of EVs participating in the Study, which lessens concerns about geographic biases that may arise in the analysis.

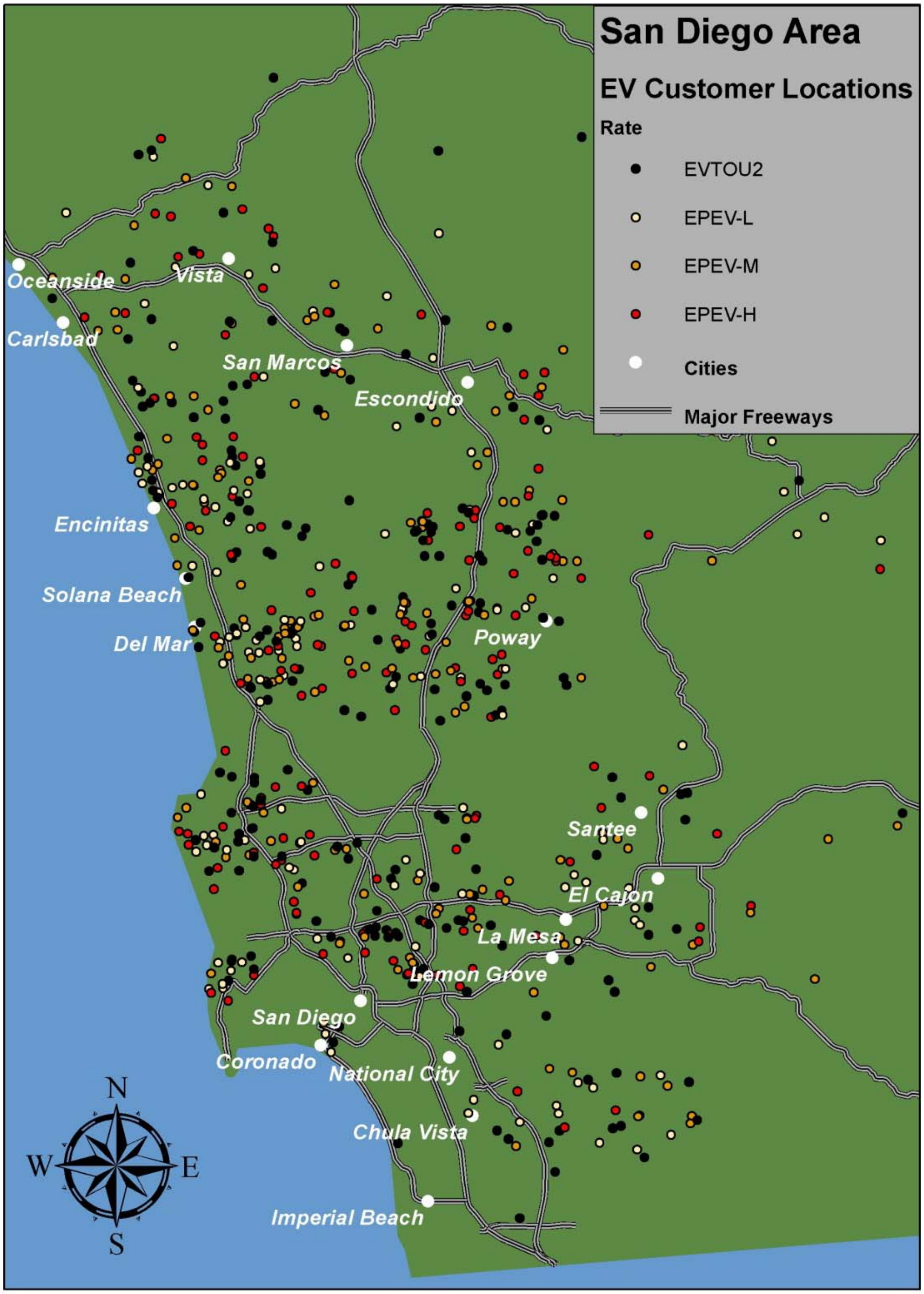
Figure 2-1: Cumulative Number of Study Participants on Experimental Rates[11]



	2011	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	2012	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	2013	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Study Participants	11	13	24	74	124	205	251	291	313	330	343	352	363	372	376	381	384	388	395	402	405	406	411	414	419	421	426	430	430	430	430	430	430

[11] The number of study participants is derived from estimated EV delivery dates and dates from billing data.

Figure 2-2: Locations of Study Participants[12]



12 Not shown in this map are Nissan LEAFs that reside in Orange County that were not eligible to participate in the San Diego-based EV Project, but are within SDG&E's service territory, a portion of these Orange County LEAFs are on the whole-house TOU rate (EV-TOU-2) and are included in the analysis in Section 4.

2.3 EV Charging Equipment

All customers in the EV Project who acquired a LEAF were offered a Level 2 charging unit for home installation (approximate value $1,499) and a DC Fast Charge port on the LEAF (approximate value $700) at no-cost, along with up to $1,200 in credit toward the installation of the equipment.[13] Upon enrollment in the Study, a charging unit was installed at the EV customer's home that provided power at 240 Volts (V) and 30-40 Amps (note that a Level 1, portable EV Cord Set is provided standard with each LEAF that conveniently plugs into a standard wall outlet at 120 V and 12 Amps). The Level 2 charging unit allows for faster vehicle charging compared to Level 1 charging and adds approximately 12 miles of range per hour of charging time compared to approximately 5 miles of range per hour of charging with the Level 1 Cord Set[14]. The installation cost for the charging unit ranges from about $600 to $2,000, 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 covered the entire cost of the installation. The customer was obligated to pay for any installation costs above $1,200.

The Nissan LEAF and charging unit both come with timers that allow customers to manage EV charging. The on-board LEAF technology allows customers to set start and/or end times for charging, as well as a maximum charge percent (e.g., 80% or 100% of the battery capacity) and the home Level 2 charging unit offers similar capabilities. Additionally, the LEAF timer has an override option should a customer decide to charge during times of day outside of the programmed charging period. This enabling technology was expected to have a strong influence on EV charging behavior by making it more convenient for them to charge during a preferred time and to take advantage of the lowest possible TOU prices.

2.4 Metering and Billing

The charging unit was installed on a dedicated circuit of the home's electric distribution system, which allowed for a second utility billing meter (in series with the main house meter) to measure the electric consumption for EV charging. Installation of the second meter socket box and safety disconnect breaker was typically performed during the same time as the Level 2 charging unit installation. SDG&E later set the billing meter after the charging station installation passed inspection by the electrical permitting authority. As part of the Study, SDG&E paid the cost of the second meter, the meter socket box and the electrical safety disconnect breaker. This metering arrangement was required for all Study participants[15].

Subtractive billing separated the EV electricity usage from the rest of the home's electricity usage, and was applied to create a separate EV usage bill for customers participating in the Study. The monthly bill contains both the usage for the home and EV, with the total cost shown separately. EV usage is broken

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13 This equipment and installation subsidy was provided by ECOtality and funded partially by DOE and partially by shareholders of ECOtality. See http://www.theevproject.com/downloads/documents/FAQ_DOE_ECOtality_The_EV_Project_20120924.pdf for more information.

14 EV range is dependent on driving style, conditions and speed, while the length of time for charging depends on the battery's state of charge at the beginning of the charging session, which rarely is low.

15 Appendix A.3 has photos of each component of the metering arrangement.

down by TOU period and the cost of the usage during that period, as well as the total cost for all EV usage that month. Figure 2-3 shows an example bill for a customer on the EPEV-M rate.

Figure 2-3: Example Bill for Study Participant's EV Charging

SDGE
A Sempra Energy utility

ACCOUNT NUMBER 1234 567 890 0
DATE DUE
Jun 20, 2012

Detail of Current Charges - Continued

Electric Service

Rate: EPEV-Residential   Climate Zone: Coastal
Billing Period: 5/1/12 - 5/30/12   Total Days: 29
Meter Number: 01234567   *(Next scheduled read date Jun 28,2012)*   Cycle: 20
Meter Constant: 1.000   Billing Voltage Level: Secondary
Circuit: 0552   *Your circuit is currently not subject to rotating outage. However, this is subject to change without notice.*
Total Usage: 289   *(Usage based on interval data)*

ELECTRIC CHARGES   Amount($)

Electricity Delivery *(Details below)*   289 kWh

WINTER USAGE	On-Peak		Off-Peak		Super Off-Peak		Amount($)
kWh used	11		64		214		
Rate/kWh	$.12687		$.11198		$.03217		
Charge	$1.40	+	$7.17	+	$6.88	=	15.45

DWR Bond Charge   289 kWh x $.00513   1.48

Electricity Generation *(Details below)*   289 kWh

WINTER USAGE	On-Peak		Off-Peak		Super Off-Peak		Amount($)
kWh used	11		64		214		
Rate/kWh	$.14365		$.05625		$.03467		
Charge	$1.58	+	$3.60	+	$7.42	=	12.60

Total Electric Charges $29.53

TAXES & FEES ON ELECTRIC CHARGES		Amount ($)
City of San Diego Franchise Fee Differential	26.92 x 5.78%	1.56
Franchise Fees on Electric Energy Supplied by Others	2.61 x 6.88%	.18
State Surcharge Tax	289 kWh x $.000290	.08
State Regulatory Fee	289 kWh x $.000240	.07

Total Taxes & Fees on Electric Charges $1.89

Total Electric Service $31.42

Customer participants were not given any "bill protection," or reimbursed for charges if they would have been less on another rate since each experimental rate offers an opportunity for EV customers to achieve savings by selecting charging times with lower price per kWh. It was essential to not provide bill protection in an effort to maintain the integrity of the research design and measure the true impact of each TOU rate. Once enrolled in the Study, all customers were given the same amount of EV TOU rate information through direct discussions with SDG&E staff, the SDG&E website, printed collateral and the monthly bill. The content of the information was timely, educational and relevant, and was refreshed at regular intervals.

2.5 Experimental Design

Table 2-1 lists details of the experimental EV rates for Study participants as well as the whole house and standard residential rates that were otherwise applicable. Participants who agreed to participate in the Study were randomly assigned to an EV experimental rate (EPEV-L, EPEV-M or EPEV-H). Early in the experiment, participants were randomly assigned to one of two rates (EPEV-H or EPEV-M) due to the prevailing concern that the population size necessary to reduce sampling error would not be achieved; after a few months of recruiting, this concern was reduced and the third rate schedule (EPEV-L) was added to the random assignment scheme with price ratios similar to the whole house 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 allows for a fully-identified demand model of charging behavior.

The three experimental rates 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, and a relatively small disincentive to charge during on-peak. During the summer, the on-peak rate ($0.25/kWh) is just under two times the super off-peak 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 ($0.28/kWh) is 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 strongest incentive for super off-peak charging and the largest disincentive for on-peak charging. During the summer, the on-peak rate ($0.36/kWh) is six times larger than the super off-peak rate ($0.06/kWh). During the winter, the on-peak rate ($0.32/kWh) is nearly five times larger than the super off-peak rate ($0.07/kWh).

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

Table 2-1: Rates Available to EV Project Participants[16]
Total Rates Effective March 1 – June 30, 2012

Period		EV-TOU-2		SDG&E Study Rates					
				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[17]	$0.25	1.84	$0.25	2.02	$0.28	3.83	$0.36	5.71
	Off-peak	$0.16	1.16	$0.16	1.23	$0.17	2.41	$0.14	2.28
	Super Off-peak	$0.13		$0.13		$0.07		$0.06	
Winter	Peak	$0.16	1.21	$0.17	1.24	$0.23	3.03	$0.32	4.83
	Off-peak	$0.16	1.16	$0.16	1.19	$0.16	2.02	$0.13	1.93
	Super Off-peak	$0.14		$0.13		$0.08		$0.07	

Period		DR
		$/kWh
Summer	Tier 1	$0.14
	Tier 2	$0.17
	Tier 3	$0.26
	Tier 4	$0.28
Winter	Tier 1	$0.14
	Tier 2	$0.17
	Tier 3	$0.24
	Tier 4	$0.26

Figure 2-4 shows the distribution of EV Project customers across rate options that were analyzed as part of this Study, as of September 24, 2013.[18] Of the 702 customers that were analyzed, 430 enrolled in an experimental rate and 272 enrolled in the EV-TOU-2, whole house rate.[19]

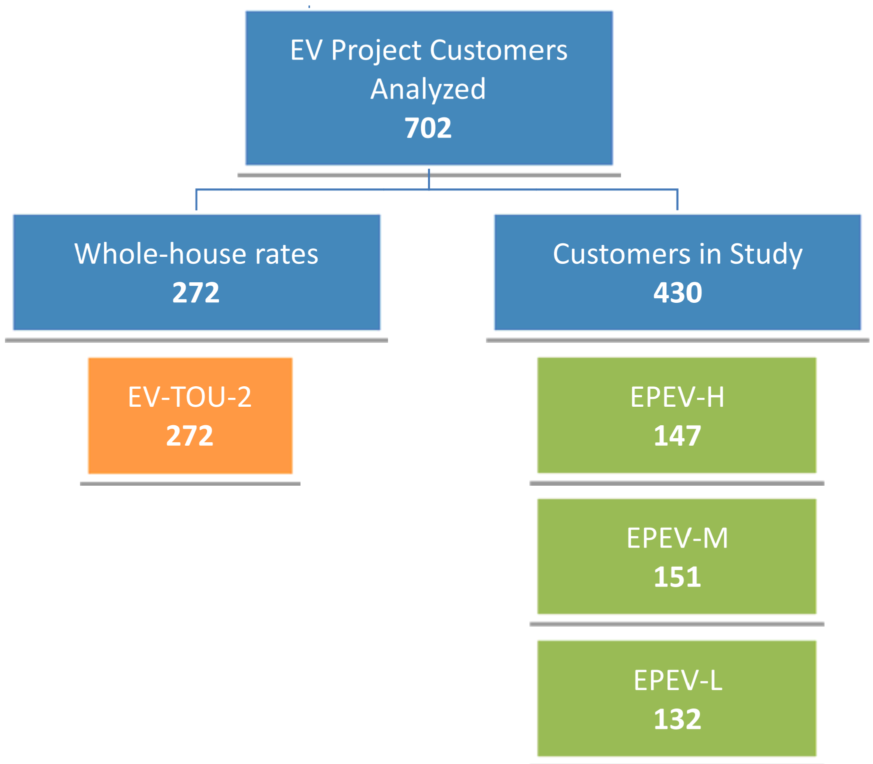
16 These rates represent the total bundled rates that include the Utility Distribution Company (UDC) charge, the Department of Water Resources Bond Charge (DWR-BC) and Electric Energy Commodity Charge (EECC) rates. Prices are rounded to two decimal places to simplify presentation.

17 The peak period for the three experimental rates was from noon to 8 PM while the peak period for the EV-TOU-2 rate was from noon to 6 PM.

18 A small number of EV Project participants remained on the non-time varying DR rate or chose SDG&E's non-pilot EV TOU rate that requires installation of a separate EV charging meter.

19 Not everyone who wanted an experimental rate was enrolled due to EVSE installation problems or costs, so it would be incorrect to conclude from this data that 39% (272/702) chose the EV-TOU-2 rate over the experimental tariffs.

Figure 2-4: Number of EV Customers Analyzed by Rate



Although not planned in the original Study design, the influence of a solar photovoltaic (PV) system emerged as an important customer characteristic that may have a material impact on EV charging. PV systems are present at 179 (25%) of EV households in the Study population, as shown in Table 2-2.[20] This is an important aspect because these customers could face significantly different incentives regarding their charging behavior. Specifically, they may or may not be more apt to charge their vehicles during the day assuming that they would be using the energy from their PV system, which could otherwise be sold back to SDG&E under a Net Energy Metering rate. Many EV Project customers who chose not to participate in the Study rates have PV systems (36%), but there is still a substantial group of customers who have PV systems and are on one of the three experimental rates. This offered another opportunity for a dedicated examination of Study participants who have PV systems.

[20] For comparison, during the course of this Study, the share of all residential customers in SDG&E service territory with solar was just over 1%.

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

Rate Schedule	Have PV System	No PV System	% Have PV System
EPEV-H	40	107	27%
EPEV-M	40	111	26%
EPEV-L	35	97	27%
EV-TOU-2	64	208	24%
Total	***179***	***523***	***25%***

2.6 Report Organization

The remainder of this report is organized into four sections and three appendices. Section 3 presents several analyses of load data associated with EV charging for customers who participated in the Study. Section 4 presents similar analyses of charging behavior, but exclusively examines whole house load data for EV customers not participating in the Study who are on a rate other than an experimental rate. Section 5 presents the findings of the economic model of EV charging that relates changes in charging behavior to differences in price. Section 6 concludes with major findings and implications for utilities. The appendices contain further details about the source of the data, the demand model and an analysis of charging behavior across different demographic groups.

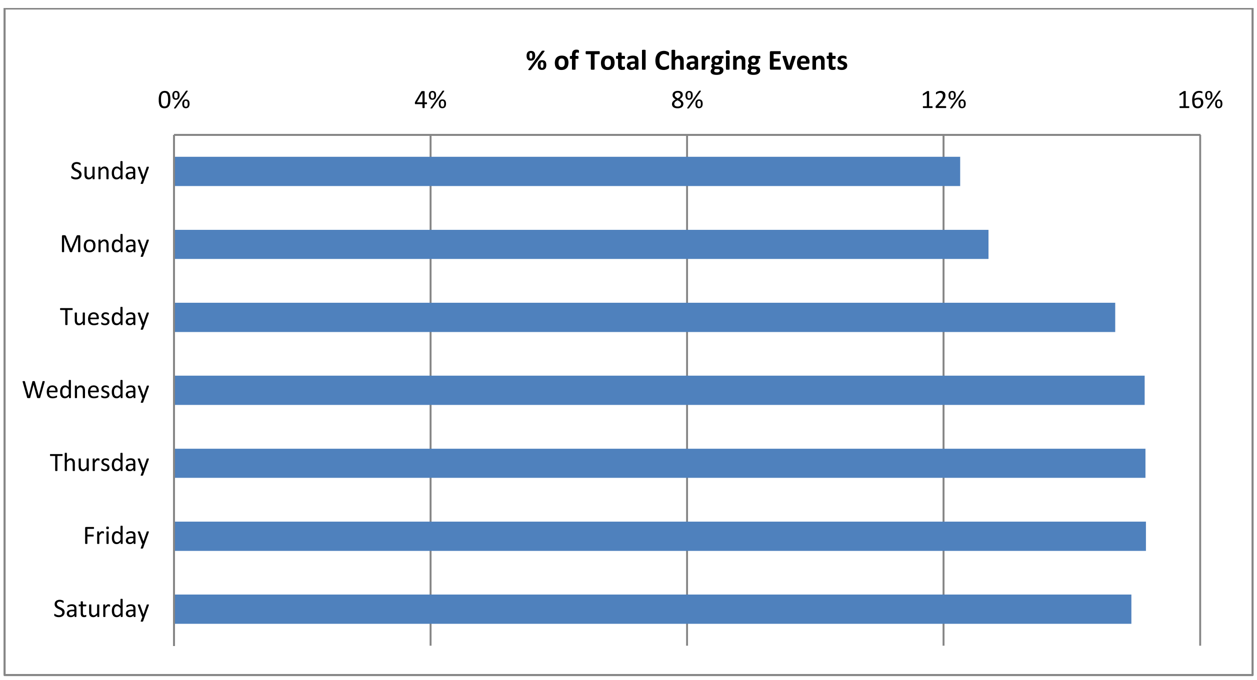
3 Analysis of EV Charging Data for Customers in Rate Experiment

This section presents descriptive analyses of EV charging load and usage data and examines important patterns in the data. All of the results presented in this section pertain only to customers in the SDG&E Study who are on experimental rates.[21] The analysis covers both those who do and do not have PV systems. Additional analysis for Study participants in support of the demand modeling is presented in Section 5. Results for the whole house, EV-TOU-2 rate group are presented in Section 4.

3.1 EV Charging Events

EV charging data was analyzed at hourly intervals to generate summary information about charging events. Any hour in which electricity use was greater than 0.4 kWh was considered part of a charging event and a set of consecutive charging intervals comprises one charging event. Figure 3-1 shows the fraction of total charging events that occurred on each day of the week. Charging events are defined by the hour when charging began. Most charging events occurred during the super off-peak period from 12 AM to 5 AM, so each day in the figure can also be interpreted as charging during the previous night. As an example, if a customer plugged in their EV at 11:30 PM Sunday and charging completed at 3 AM Monday, that charging event was counted as occurring on Sunday. Of note is that charging events are less frequent on the weekends (e.g., Saturday night into Sunday morning and Sunday night into Monday morning) than during the work week of Monday through Friday.

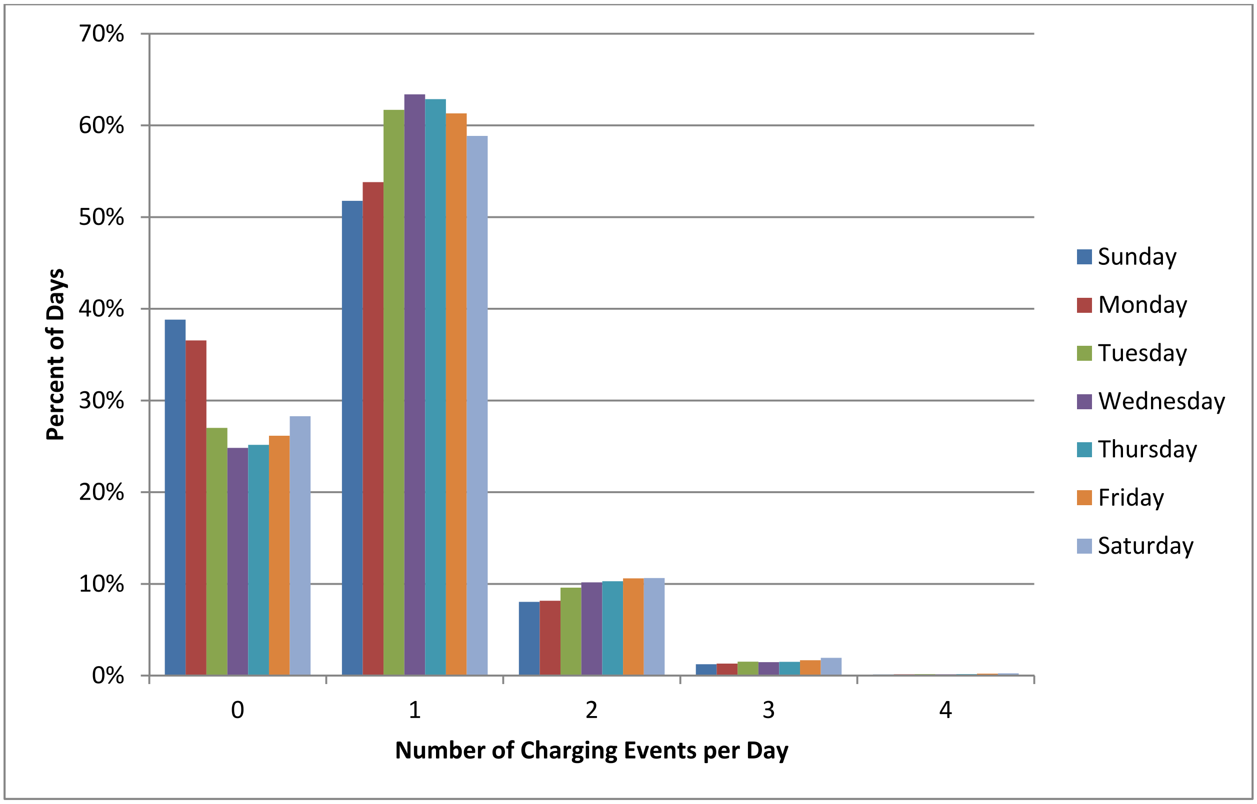
Figure 3-1: EV Charging Events by Day of the Week



21 Unless otherwise stated, graphs and charts display information for all customers on experimental rates using only days during which charging activity occurred.

Figure 3-2 shows the number of distinct charging events per day for each day of the week. The denominator used for making the graph is the total number of customer-days, which is equal to the number of days multiplied by the number of customers in the Study.[22] An important finding is that there are a significant number of customer-days where no EV charging occurred. On days when EV customers did decide to charge their vehicles, they generally charged the vehicle in one charging session rather than multiple charging sessions.

Figure 3-2: EV Charging Events per Day



At a more granular level, it is useful to examine the exact time when EV charging events began as well as their duration. Figures 3-3 and 3-4 show the distributions of EV charging event start times and durations across each of the three experimental rate groups for both PV and non-PV customers.[23] The most common time for charging to begin in all rate groups was the super off-peak period, when 65-80% of all charging events began (see Figure 3-5). Few charging events began during the on-peak and off-peak periods. For non-PV customers, the only noticeable difference across rate groups is that the percentage of charging events beginning between 12 AM and 1 AM gradually increases as the TOU price ratio

[22] For example, the graph shows that on 39% of Sunday customer-days there were no charging events and on 51% of Sunday customer-days there was only a single charging event per day.

[23] Throughout the analysis "Non-PV customers" refer to customers who do not have a PV system at the time of interest. Customers who install a PV system after acquiring their EV will therefore be Non-PV owners for the days prior to when the PV was installed and PV owners for the days after the installation. Out of the 179 customers in the Study who have a PV system, approximately 75% installed their PV system before EV charging events began.

increases, going from <50% for EPEV-L customers up to 60% for EPEV-H customers (see Figure 3-3). PV and non-PV customers exhibited only minor differences in when they decided to start charging their vehicles. In terms of duration, the average charging event lasted approximately 3 hours and 10 minutes and eighty percent of charging events were four hours or less (see figure 3.4).

Figure 3-3: Start Times of EV Charging Events

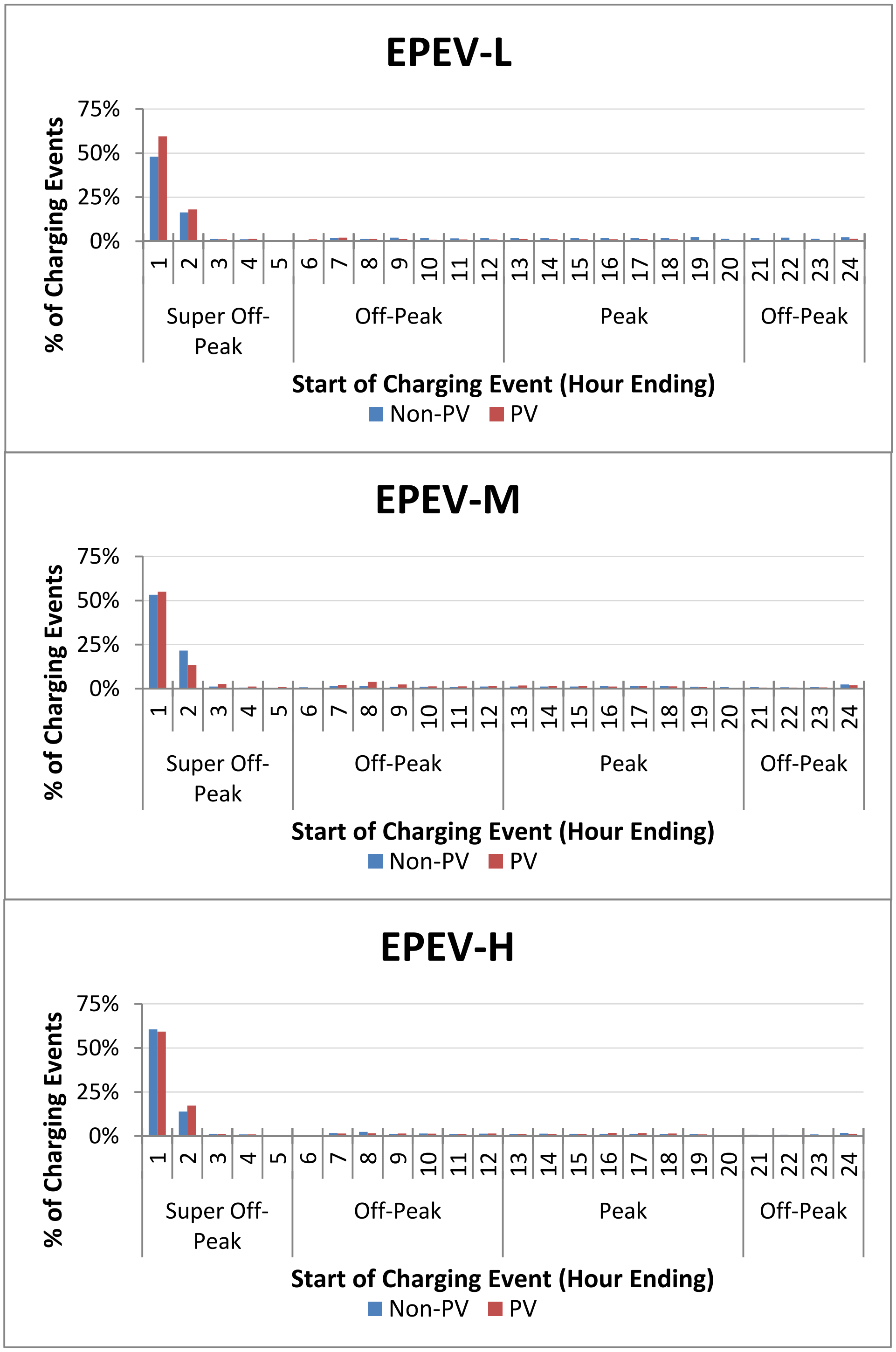
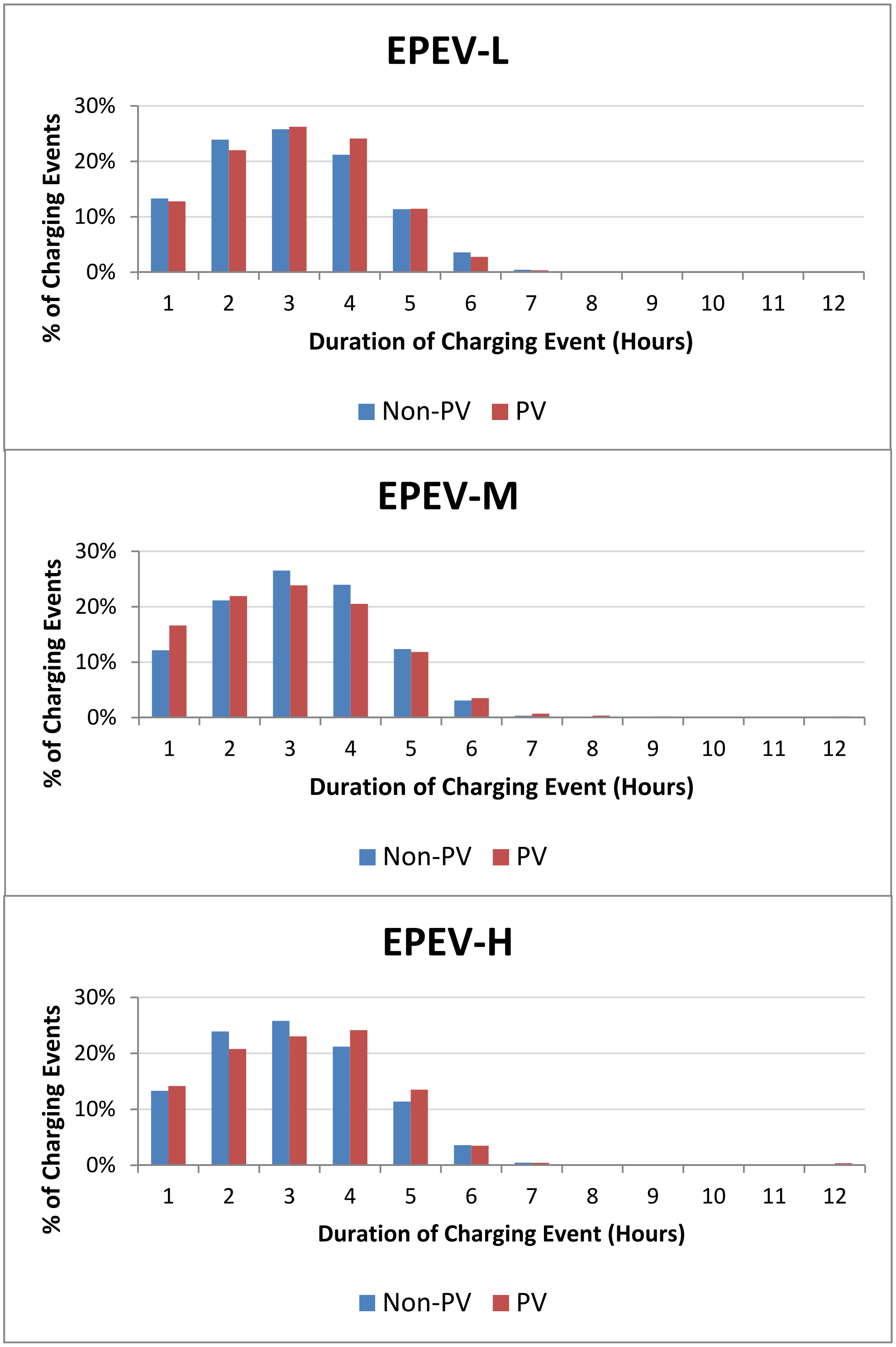
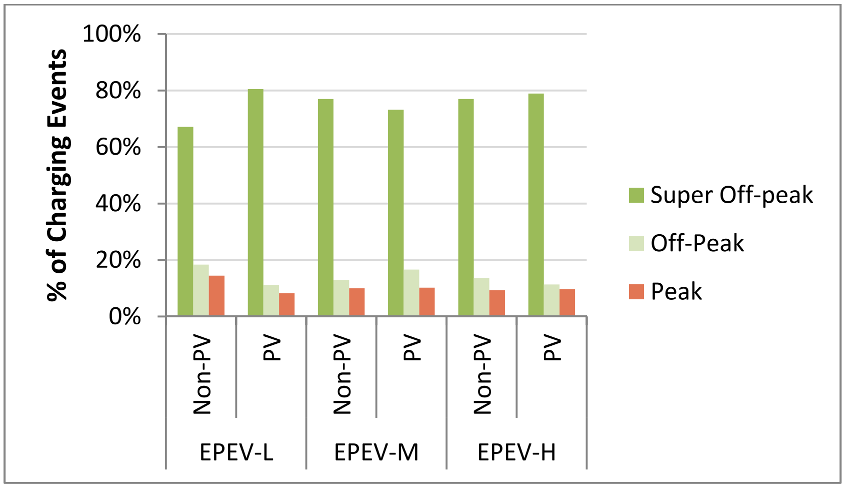


Figure 3-4: Duration of EV Charging Events



Note: The interval data used to make this figure is at the hourly level. Because of this, the duration of charging events were rounded up to the nearest whole number. For example, a charging event that began at 12:30 AM and ended at 3:45 AM (3 h, 15 m) was classified as a 4-hour charging event in the figure.

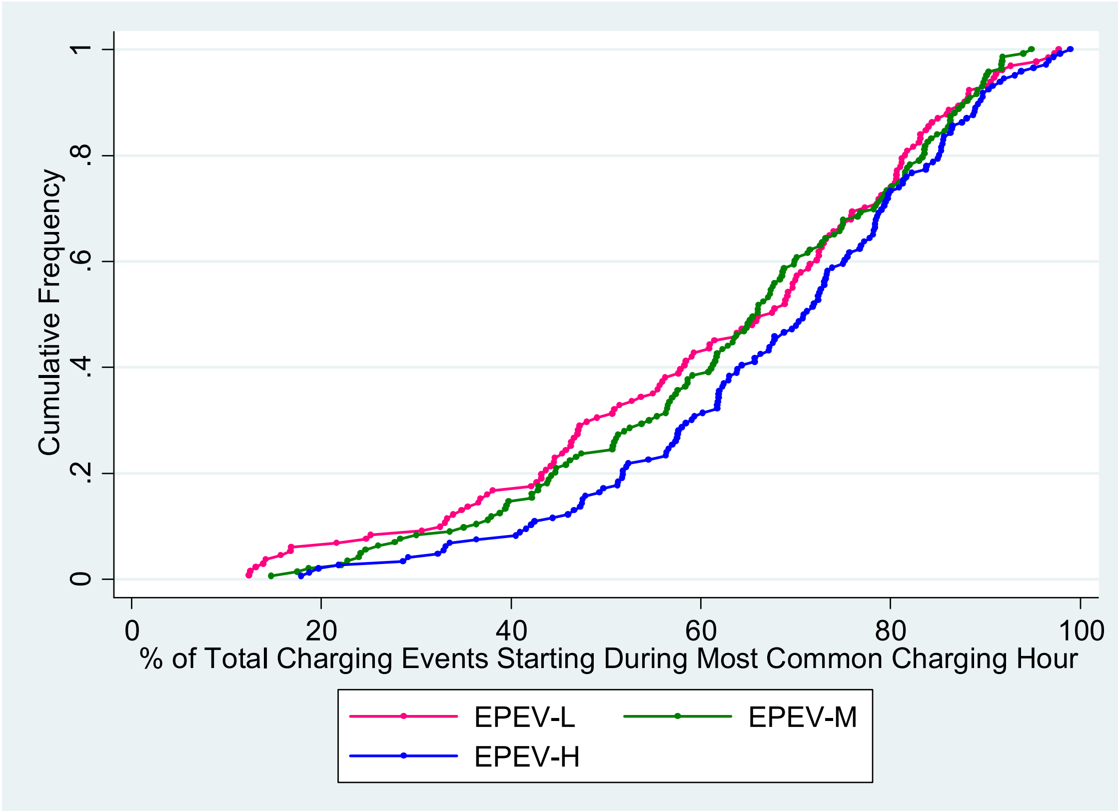
Figure 3-5: Start Times for EV Charging Events by Rate Period



The fact that so many charging events started at the beginning of the super off-peak period, which is also at a time of day that would be inconvenient for many customers to manually initiate charging, suggests that EV customers regularly used the timers on either their EV or charging station. To further investigate the degree to which timers were used, the start times of charging events for each individual EV customer were analyzed. It was expected that customers who used timers regularly would generally start charging their EVs at or around the same time each day, that is, they would exhibit very consistent charging behavior. To quantify this consistency, hourly interval data was used to identify the most common start hour for charging and the share of that owner's total charging events that began during that hour. Given that 60-80% of charging events start during the super off-peak period (Figure 3-5), this regularity is very likely due to timer usage.

Figures 3-6 shows the cumulative frequencies for the measurement of charging consistency grouped by rate. The x-axis shows the percentage of a customer's charging events that started during that customer's most common start time. For example, suppose an EV customer had 10 total EV charging events with six events starting between 12 AM and 1 AM, three events starting between 6 AM and 7 AM and one event starting between 8 PM and 9 PM. For this customer, the most common start time was between 12 AM and 1 AM and the percentage would be 60%. Lines further to the right in the graph indicate more consistent charging behavior. The figure suggests that customers facing TOU rates with higher price ratios used their timer more regularly (or possibly over-rode their timer setting less frequently). A similar analysis was conducted comparing weekday charging with weekend charging and showed charging behavior on weekdays was slightly more consistent than charging on weekends, across the three rates.

Figure 3-6: Consistency of Charging Start Times



3.2 Average Load Shapes

Average daily EV load shapes for each experimental rate group on days when EV charging occurred are shown in Figure 3-7.[24] Overall, EV charging loads were very similar for customers facing each of the different TOU rates. However as the TOU price ratio increased, customers tended to do more charging during the super off-peak period. EPEV-L customers also charged slightly more during on-peak and off-peak times than EPEV-M and EPEV-H customers.[25]

Figure 3-8 presents average EV loads for each day of the week. In general, the majority of EVs in the Study began charging immediately after 12 AM although, as seen Figure 3-3, about 20% of participants began charging between 1 AM and 2 PM, which explains the increase in load in the first two hours in Figure 3-8. After 2 AM, charging loads gradually declined as cars became fully charged until 6 AM, at which point most EVs ceased charging and do not charge again that day. The slight increase in loads after 11 PM suggests some customers initiated charging prior to 12 AM. Customers on EPEV-H and EPEV-M rates appeared to have nearly identical average EV loads, whereas customers on EPEV-L rates

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[24] We exclude all observations where total charging consumption over the course of the day is less than 1 kWh. We refer to days with usage greater than or equal to 1 kWh as a charging day and those below as non-charging days.

[25] Descriptive graphs of these differences are shown in Section 3.2 and formal hypothesis tests are performed in Section 3.3.

had lower average loads after 12 AM and slightly higher average loads in the evening off-peak hours prior to 12 AM. The total level of charging usage is similar across the three groups, but there was a noticeable small increase in off-peak and on-peak charging on weekends for all rate groups. Non-charging days were included in this figure to capture the fact that EVs were charged less often on Sunday and Monday, likely reflecting lower EV usage on weekends compared to weekdays. Figure 3-9 shows average load shapes split out by season; there were no discernible differences in loads.

Figure 3-7: Average Daily EV Load Shapes on Charging Days

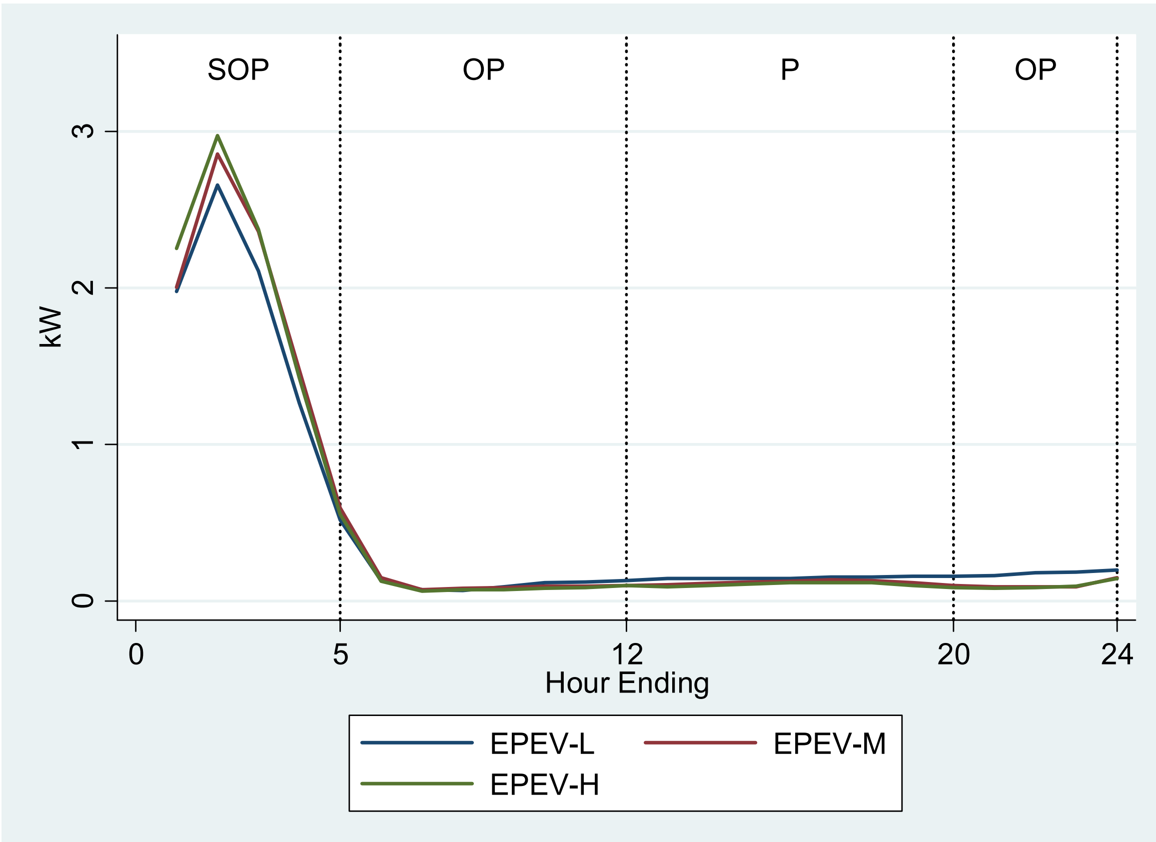
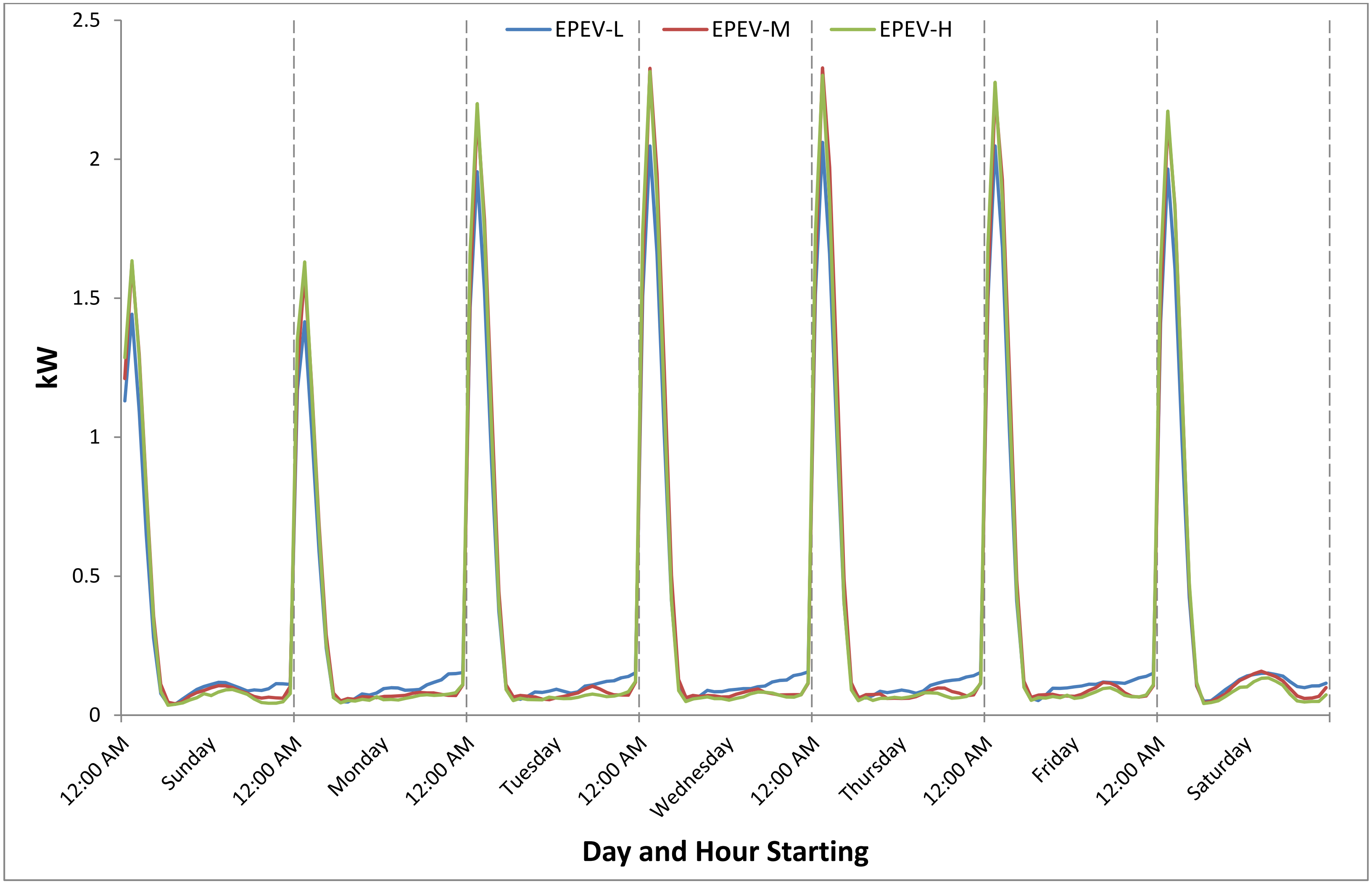


Figure 3-8: Average EV Load, by Rate Schedule and Day of Week (Charging and Non-Charging Days[26])



26 This graph contains both charging and non-charging days in order to capture the relative amounts of charging that took place on each day of the week.

Figure 3-9: Average EV Load Shape by Season on Charging Days

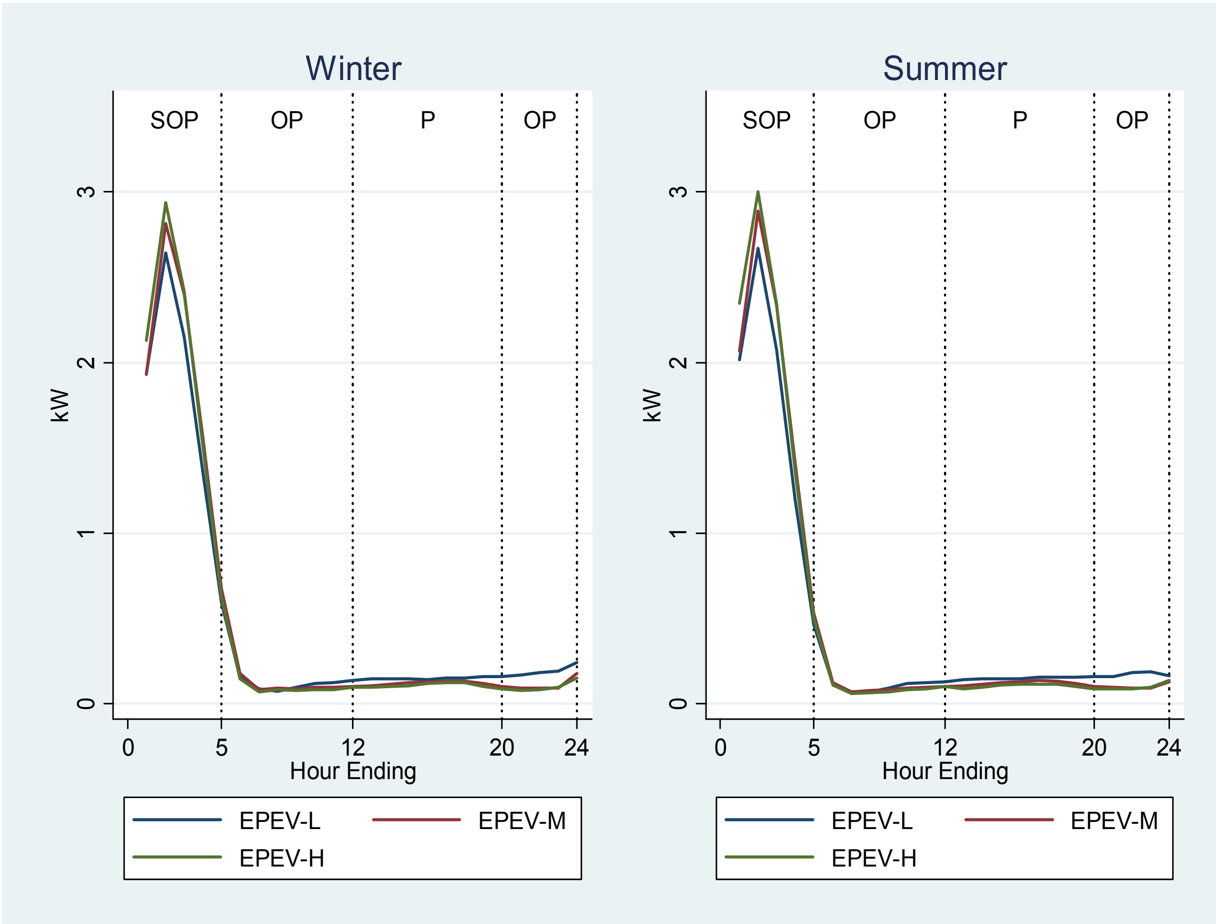


Figure 3-10 presents the average proportion of daily EV loads by rate period for all weekdays and weekends in which charging activity occurred. Overall, EPEV-H and EPEV-M customers conducted 85% and 83% of their EV charging activity during super off-peak hours, respectively. For EPEV-L customers, 78% of charging occurred during super off-peak hours. The differences in the amount of super off-peak charging between the customers on EPEV-L and the other two rates are statistically significant at the 5% level. This suggests that the lower rates faced by the EPEV-L customers outside of the super off-peak periods made them more likely to charge during the peak and off-peak hours.

Figure 3-11 shows the average load shapes for Study participants for non-PV and PV customers, pooled over rate groups, day types and seasons. The shapes are almost identical, indicating that on average, PV customers with separately metered EV charging load and billed separately from the house usage exhibited very similar charging behavior as non-PV customers. The similarity in average charging behavior between PV and non-PV customers may be due to three factors: PV customers are just as likely as non-PV customers to use their EV for commuting to work so that they are not home to charge during normal business hours; PV net energy metering and billing does not apply to EV charging decisions due to the separate EV metering and pricing; and PV owners also have EV and charging timers that are easy and effective to use. The issue of how PV ownership affects EV charging time decisions for customers with whole house EV-TOU-2 rates is discussed in greater detail in Section 4 and the impact of PV ownership on EV price responsiveness is discussed in Section 5.

Figure 3-10: Average Proportion of Daily EV Energy Consumption by Rate Period on Charging Days

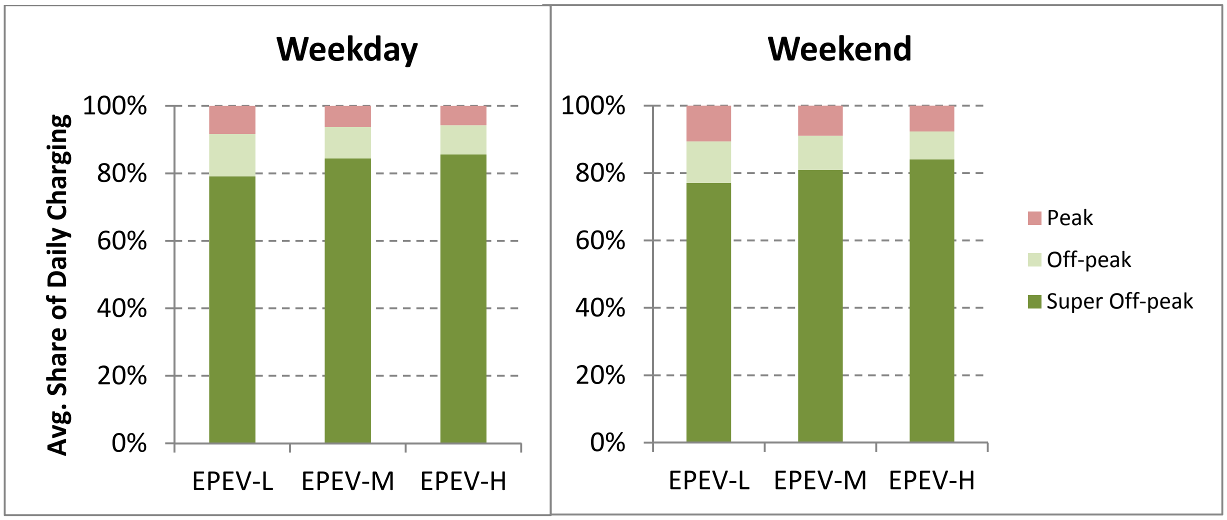
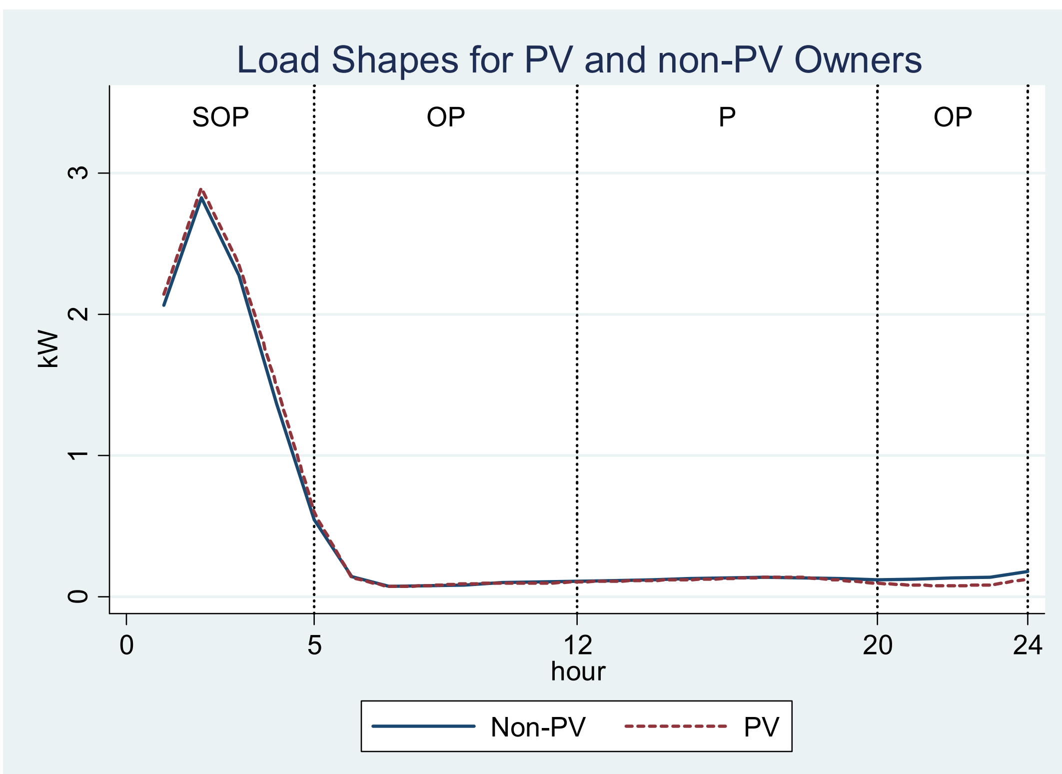


Figure 3-11: EV Charging Load Shapes for Non-PV and PV Owners on Charging Days



Finally, it is interesting to compare load profiles for customers who charge their EVs with different degrees of consistency. Using the measure of consistency defined in Section 3.1, Figure 3-6, if less than 33% of events started during the most common start period for a customer, they were defined as

"Inconsistent". "Moderately Consistent" was defined as having between 33% and 67% of charging events occurring during the most common start period, and "Very Consistent" was defined as having more than 67% of charging events starting during the most common start period. It is expected that customers who are very consistent would charge almost exclusively during the super off-peak period, while inconsistent customers would charge more often at other times of the day. Figure 3-12 shows the average load shapes for each of these consistency groups. Sample sizes for each group are included in the legend and show that 92% of EV customers display either moderate or very consistent charging behavior. As expected, the inconsistent group charged more during on-peak and off-peak hours relative to the other two groups, but still have a small peak during the super off-peak period. One possible way in which customers in these consistency groups could be different is the prevalence of PV ownership in each group. As shown in Table 3-1, however, PV ownership across the three groups is essentially the same. A simple Chi-squared test fails to reject the null hypothesis that the shares of PV ownership in each group come from the same underlying distribution (p-value = 0.926), meaning that PV ownership does not explain whether customers exhibit consistent or inconsistent charging behavior.

Figure 3-12: Avg. Load Profiles for Different Consistency Groups on Charging Days

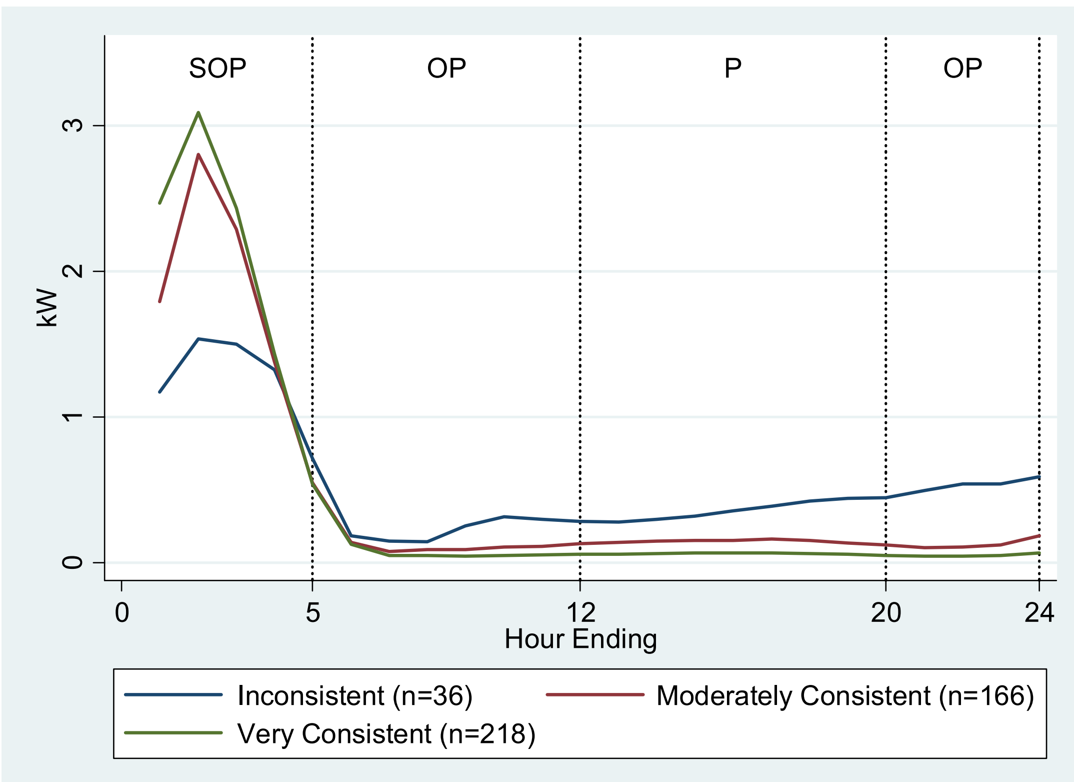


Table 3-1: PV Ownership for Different Consistency Groups

PV ownership	Inconsistent (n=36)	Moderately Consistent (n=166)	Very Consistent (n=218)
Does not own PV	66.7%	68.7%	69.7%
Owns PV	33.3%	31.3%	30.3%

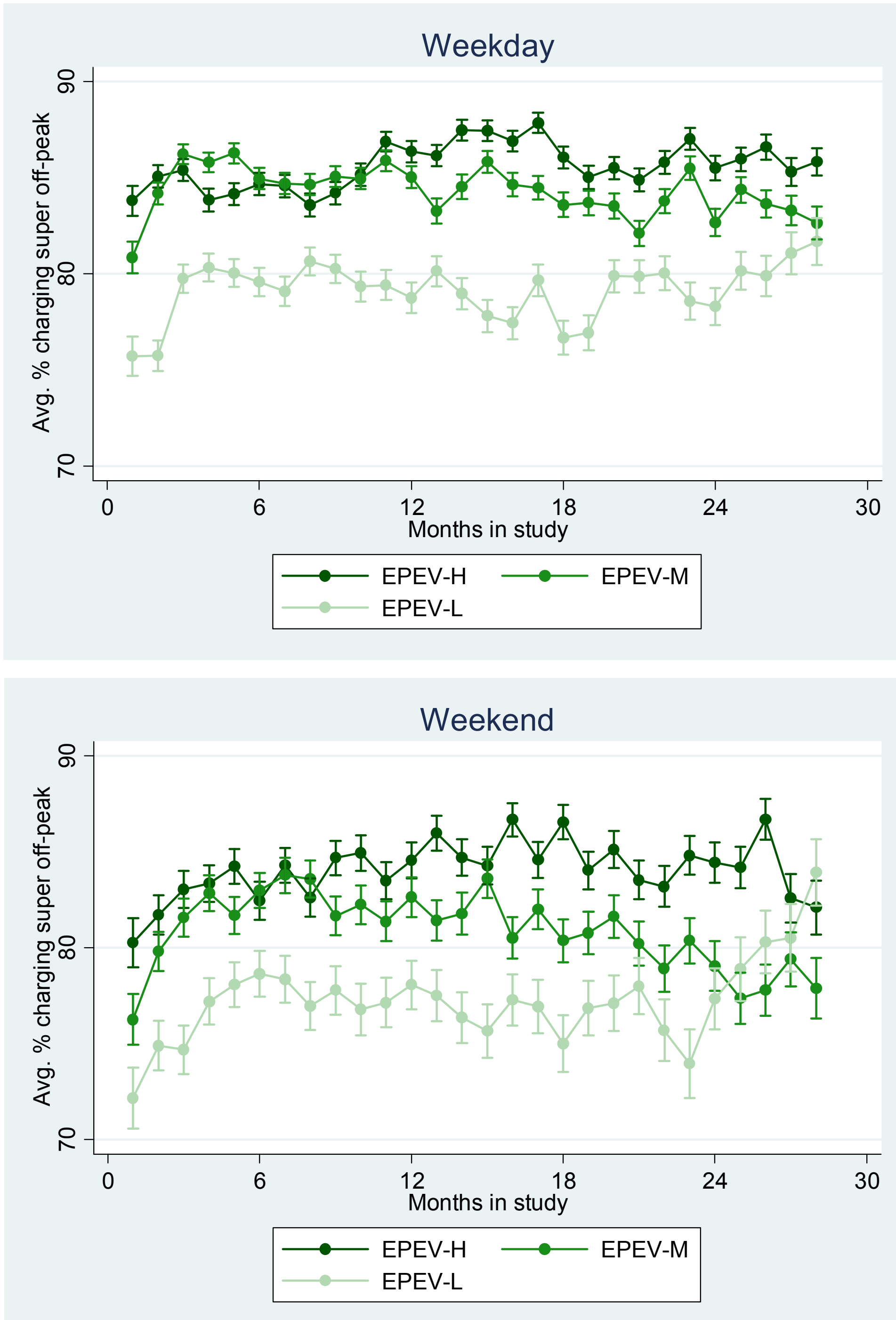
3.3 Dynamic Load Analysis

The figures presented in the previous section provide many insights into how EV customers charge their vehicles at home, the impact of TOU rates and the importance of enabling technology (in this case charging timers), but they provide only a static view of EV charging behavior. Another important dimension to consider is time. In particular, it is important to explore whether EV charging behavior is changing over time and whether or not the patterns shown in the static analysis are persistent. This section addresses these topics by primarily analyzing EV loads as a function of the amount of time that a customer remains in the Study. The focus of this section is on the share of EV charging that occurred in the on-peak and super off-peak periods for each of the rate groups.

Figure 3-13 presents the average super off-peak proportion of daily EV loads on charging days by the number of months after the first charging session and provides several insights (the bars in the figure represent 95% confidence intervals around each mean). First, EPEV-L customers had slightly lower levels of super off-peak charging while customers on the higher on-peak to super off-peak price ratios had higher shares of super off-peak usage and this separation persisted for more than two years. Second, there is a clear upward trend in the share of super off-peak usage for all rate groups during the first 3–4 months that a customer was enrolled in the Study, with increases in the share of super off-peak charging ranging anywhere from 4–10%. One interpretation of this result is that EV customers went through a learning phase related to how they use their vehicle, how their TOU rate works in light of feedback from the monthly bill, or how to best use their charging timer (or whether to use it at all). In this context, learning manifests itself as increases in super off-peak charging and decreases in on-peak charging from month to month. After the first few months, super off-peak charging shares remained relatively stable for each rate group over the remainder of the Study period.

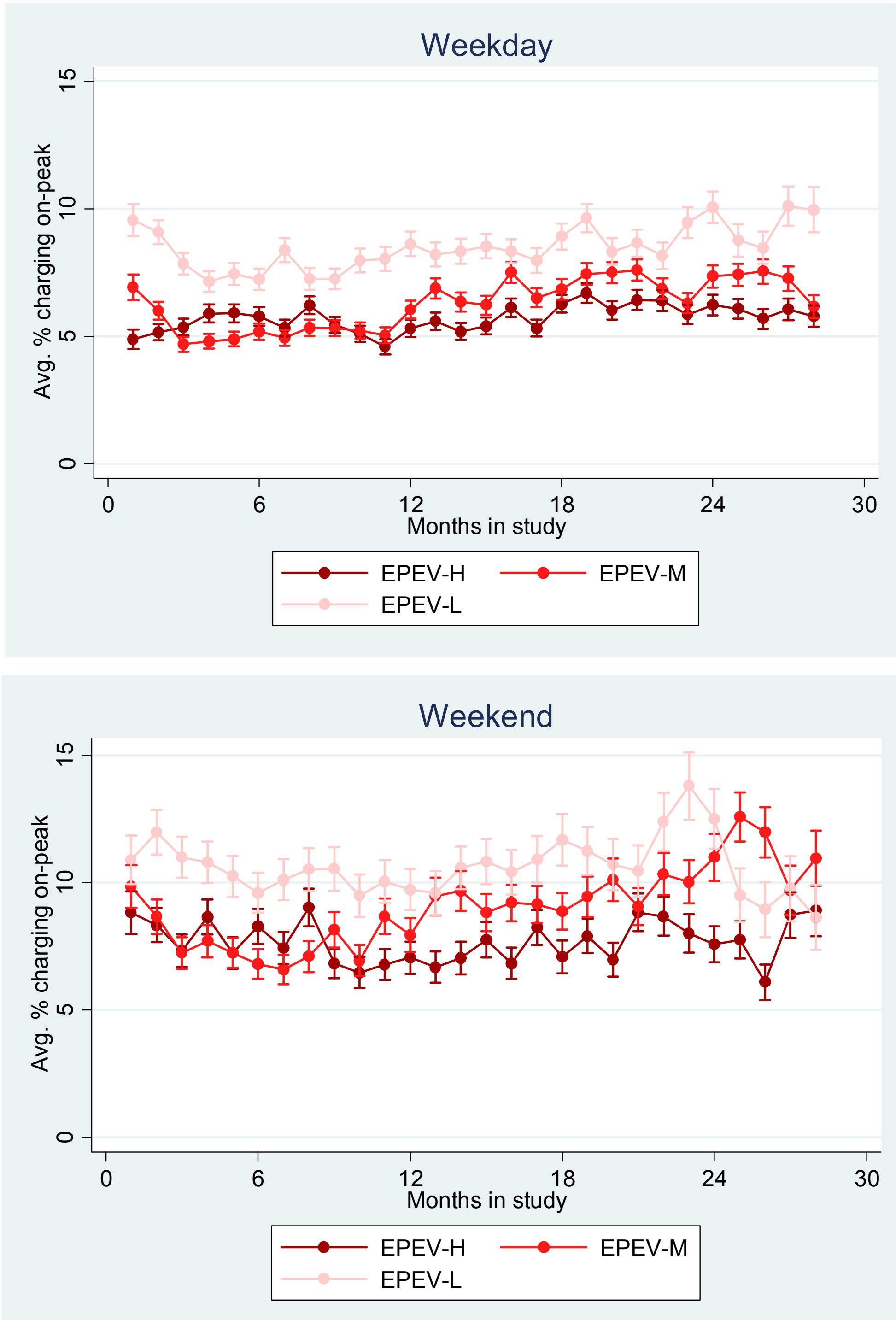
Figure 3-14 shows a similar graph for the share of charging done during the on-peak period. Again, the separation of usage patterns between EPEV-L customers and EPEV-M and EPEV-H customers on weekdays persists for the duration of the Study; there is also a pronounced learning phase during the first few months for EPEV-L and EPEV-M customers. Levels of on-peak charging on the weekend tended to be higher than during the week and exhibited a pattern with considerably more variability. Also, it is interesting to note the slight upward trend in on-peak charging after the learning phase instead of a leveling off that was observed for super off-peak charging. For most of the groups, the share of EV charging in the on-peak period after being in the Study for more than two years was about the same as it was during the first month, effectively eliminating any reduction in on-peak charging that occurred during the learning phase. Because there is no corresponding decrease in the share of super off-peak charging in Figure 3-13, this gradual increase in on-peak charging must be coming at the expense of off-peak charging.

Figure 3-13: Average Super-off Peak Proportion of Daily EV Energy Consumption on Charging Days, by Months on Rate[27]



27 The sharp upturn at the right hand side of the graph for the EPEV-L group on weekends reflects the behavior of the small sample of customers that were the first to join the study. This probably reflects their steady state behavior at the end of their initial learning period, which became masked in the graph by the behavior of new entrants, rather than some change in behavior near the end of the study period.

Figure 3-14: Average Peak Proportion of Daily EV Energy Consumption on Charging Days, by Months on Rate[28]



[28] Similar to Figure 3-13, the sharp downturn at the right hand side of the graph for the EPEV-L group on weekends reflects the behavior of the small sample of customers that were the first to join the study. Together with Figure 3-13, the figure suggests that early adopters substituted super off-peak charging for charging during the peak period.

To formally test for differences in charging shares between the three rate groups, a regression model was estimated on the monthly data shown in Figure 3-13 with dummy variables denoting a customer's rate included as regressors. Using monthly observations for each customer provides a panel data set that allows for the use of a more powerful regression model.[29] The estimated coefficients from this model provide measures of the average differences in percentage charging shares between customers on different rates. These differences were obtained using a random-effects model[30] incorporating panel-corrected standard errors with individual-specific AR1 corrections to account for the fact that the observations for a given individual over time are likely to be related to each other.[31,32] The t-statistics for the rate dummies provide pairwise tests of differences in the impacts of the rates. These differences are shown in Table 3-2, which shows that the impacts of the three rates on charging shares are statistically different from one another, mostly at a significance level of 1%. The EPEV-H rate induced more super off-peak charging and less on-peak charging than both the EPEV-L and EPEV-M rates. The estimated differences in the table can be interpreted as causal given the randomized experimental design of this Study. For example, the EPEV-H rate increased the share of weekday charging during the super off-peak period by 6% compared to the EPEV-L rate and almost 2% compared to the EPEV-M rate.

Table 3-2: Tests of Pair-wise Differences in Percentage Charging Shares between Rates

Day Type	Charging Share	EPEVL – EPEVM	EPEVL – EPEVH	EPEVM – EPEVH
Weekday	% Peak	1.80	3.08	1.29
	% Super Off-Peak	-4.16	-6.04	-1.87
Weekend	% Peak	2.33	3.25	0.92
	% Super Off-Peak	-4.06	-6.62	-2.55

= Significant at 1%

= Significant at 5%

= Not Significant at 5%

To formally test for the presence of a learning effect, a regression model with random effects was estimated for each rate group containing three explanatory variables: the number of months in the Study, a dummy variable denoting whether a given month is one of the first four months for an

29 Panel data is defined as data containing multiple observations over time for each unit of analysis. The term "panel" refers to a unit of analysis. In this case the panels are the EV customers and each customer has monthly observations.

30 The two most common panel regression models used are the fixed effects model and the random effects model. Each assumes that there are unobserved characteristics of each individual that influence the outcome of interest. The random effects model assumes that these characteristics are not related to a customer's rate, which is a good assumption in this case due to the random assignment of rates.

31 Panel data observations are likely to be related in two different ways. First, each individual has their own unique characteristics and circumstances that will be important determinants of their charging patterns in every month. Second, charging behavior for an individual in any given month is likely to be related to that individual's charging behavior in previous months. This second data feature is known as autocorrelation (or serial correlation) and is a common issue when analyzing observations over time. An AR1 process is one where an observation in any given month is affected by the observation in the previous month. An AR2 process is when an observation is influenced not only by the previous observation, but also the observation two periods ago.

32 An alternative model that could be used is a panel regression model with random effects and robust standard errors. Random effects are valid in this circumstance because individuals were randomly assigned to different rates. This model was also estimated and yields the same qualitative results as the PCSE model.

individual (call this the "learning phase") and an interaction term between these two variables. The coefficients of interest in this model are the learning phase dummy and the interaction term. A significant coefficient on the dummy variable indicates that the average charging share during the learning phase is significantly different from that same charging share over the remainder of the Study duration and a significant interaction term means that there is a different time trend for charging shares during the learning phase. Larger values of the coefficient on the dummy variable signify a greater amount of learning. Table 3-3 shows these coefficients for each of the charging shares in each of the rate groups. The results show significant average learning effects for customers on the EPEV-L and EPEV-M rates for both on-peak and super off-peak charging, but weaker learning effects for those on the EPEV-H rate. For EPEV-L and EPEV-M customers, the average share of on-peak charging in the learning phase is about 3% higher than during the remainder of the Study duration, while the average share of super off-peak charging is 6-7% lower. The slope coefficients on the interaction term provide measurements of the rate at which learning occurs. During the learning phase for EPEV-L and EPEV-M customers, the share of super off-peak charging increases by 1.8-2.9% per month and the share of on-peak charging decreases by 0-1.3% per month compared to the remainder of the Study duration.

Table 3-3: Tests for Learning Effects

		EPEV-L		EPEV-M		EPEV-H	
Day Type	Charging Share	Avg. Learning effect	Slope	Avg. Learning effect	Slope	Avg. Learning effect	Slope
Weekday	% Peak	-3.12	-0.91	-3.51	-1.05	-0.14	0.09
	% Super Off-Peak	6.15	1.84	6.87	2.18	3.95	0.99
Weekend	% Peak	-3.13	-0.52	-5.30	-1.29	-2.85	-0.66
	% Super Off-Peak	9.72	2.47	10.50	2.90	6.35	1.57

= Significant at 1%

= Significant at 5%

= Not significant at 5%

4 Analysis of Whole-house Data for EV-TOU-2 Customers in the EV Project and Not in the Study

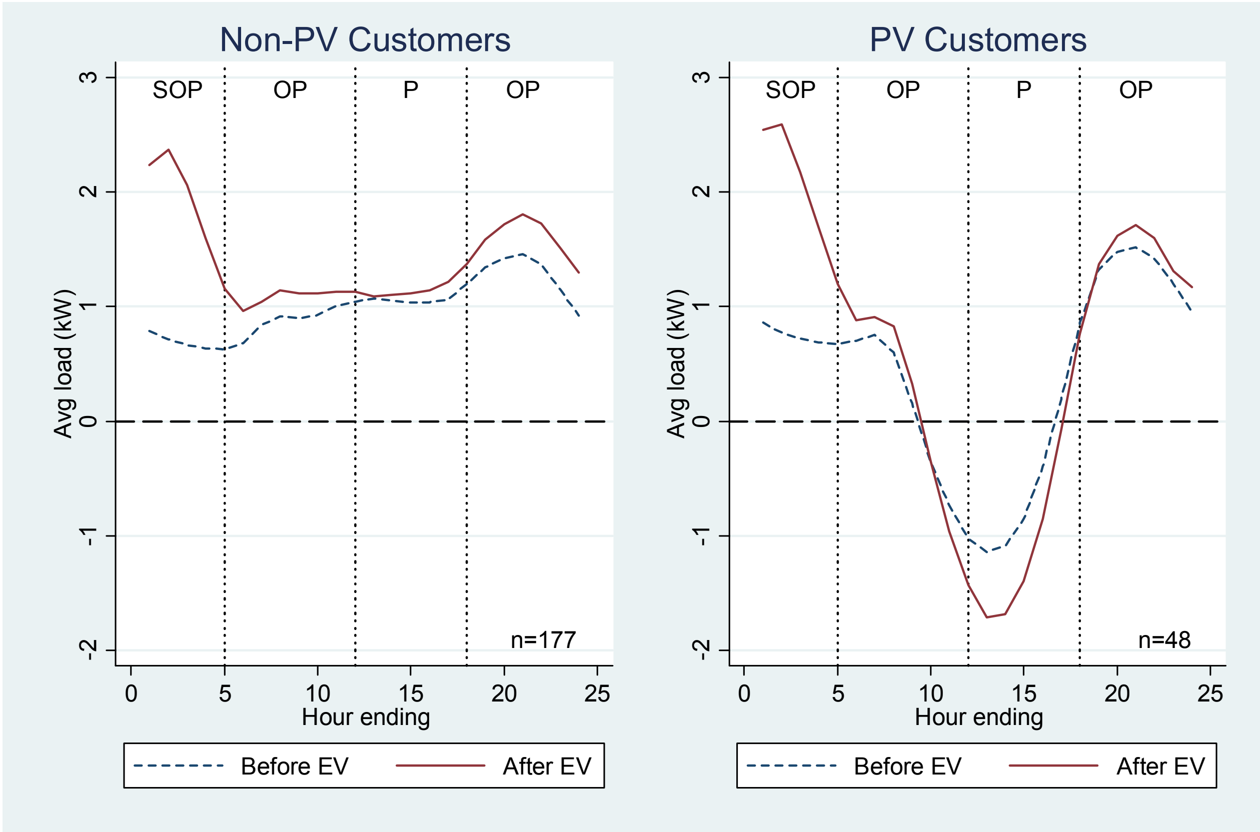
As discussed previously, in addition to customers in one of the three experimental rate groups (EPEV-L, EPEV-M and EPEV-H), some EV customers who were screened to participate in the EV Project either chose not to participate in the Study or had home configurations that did not lend themselves to the installation of a separate meter and disconnect breaker serving the charging station. These customers were given the choice to either enroll in a whole-house TOU rate (EV-TOU-2) with prices almost identical to the EPEV-L rate, or remain on the standard, tiered residential rate that does not vary over time of day. This section presents analysis of EV charging behavior for the group that enrolled on the whole-house TOU rate (i.e., the entire household usage is subject to a TOU rate structure).

Because this group was not in the Study and was not randomly assigned to an experimental EV rate, there are several limitations in comparing EV-TOU-2 customers to the Study customers. These limitations are noted and discussed throughout this section with the primary focus on drawing conclusions *within* the EV-TOU-2 group based on data before and after acquiring an EV.[33]

Figure 4-1 shows the load profiles for EV-TOU-2 customers before and after the acquisition of an EV, split out by PV ownership. To account for seasonal load patterns, only customers having 9 months of data pre- and post-EV acquisition were included. For this group, customers were on the DR rate prior to acquiring an EV and then switched to the EV-TOU-2 rate after receiving their EV. Thus, the “After EV” load profile in each panel in Figure 4-1 captures not only the impact of the EV load, but also non-EV load (other household end-use) responses to the price signals in the TOU rate. Still, the figure provides some interesting insights into the overall household load impacts of acquiring an EV.

[33] Such a pre/post analysis is also vulnerable to making incorrect statements about the *causal* impacts of EVs on whole-house electricity consumption. Because of this, most of the analysis in this section should be treated as descriptive.

Figure 4-1: Whole House Loads for EV-TOU-2 Customers Before/After EV Acquisition



Load profiles changed significantly after the acquisition of an EV. For non-PV customers, peak load moved from 7–9 PM to 12–2 AM and average loads increased during all hours of the day. The largest increases other than between 12 AM and 5 AM occurred during the off-peak period and there were relatively smaller increases during the on-peak period. This is almost certainly due to consumers shifting EV charging (and/or shifting non-EV electricity consumption) away from the peak period in response to the price signals of the whole house EV-TOU-2 rate.

For PV customers, there was a particularly large peak during the super off-peak period after acquiring an EV and then switching to the EV-TOU-2 rate. Consumption increased during both of the off-peak periods, but decreased during the on-peak period (e.g., houses are sending *more* power back to the grid). Customers certainly had an incentive to reduce peak consumption because of the whole house EV-TOU-2 rate, but this result may also be partially due to selection bias – while some customers on the EV-TOU-2 may have preferred one of the experimental rates (but could not be on one due to installation limitations noted above), others may have preferred the whole house rate because they had relatively larger peak loads that could be easily shifted to off-peak periods.

5 Electricity Demand Model

Although descriptive graphs and statistics of EV charging load are highly informative about participant behavior, it is important to understand how the results can 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 for EV charging would respond to a range of TOU rate prices.

This section describes the methodology for estimating a structural economic model of demand for EV charging within the Study and its EV TOU rates. First is a description of the model used for the analysis, followed by a description of the estimation procedure. The final subsection contains results from the estimation and puts them into a broader context.

5.1 Model Description

To estimate the effects of TOU pricing on EV charging behavior using the available data, a structural economic model of demand is specified in which consumers choose the amount of EV charging in each TOU period with the goal of minimizing the total cost of EV charging given the prices in each period and driver-specific factors, such as the need for use of a vehicle, the schedule of the customer/driver and the current state of charge in the EV. The prices affecting this decision are known and enter the model directly, whereas the driver-specific factors are unobserved and are captured by parameters estimated by assuming cost minimizing behavior on EV charging decisions.

Focusing on the price-related aspects of the EV charging decision, EV customers made trade-offs between charging during convenient times and charging during less expensive periods. These trade-offs can be captured and quantified by using price elasticities. Price elasticities measure the responsiveness of purchase decisions to a change in the price of a particular good. In this case, elasticities show how the quantity of EV charging during one period changes when the price of EV charging changes during that same period (own-price elasticity) or during another period (cross-price elasticity). It is important to recognize that the amount of EV charging a household does at any time is determined both by how much it costs at that time (including opportunity costs) 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. Charging very early in the morning is almost certainly more attractive than driving home from work in the middle of the day to charge. So, a customer's EV charging at any given time is determined by the entire schedule of prices and costs that the household faces, rather than just by those in the current period.

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 rate experiment in the context of elasticities of demand for other consumer goods. Elasticities of demand are influenced by a number of factors, such as:

- **Availability of substitutes:** customers will be more sensitive to changes in price (more elastic) with the availability of close substitutes (e.g., charging in one time period can be a close substitute for charging in another time period);

- **Percentage of income:** customers will be more sensitive to the price of a good the higher the expenditure share 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 an increase in price will result in a decrease in demand. For example, the value of -0.1 for salt tells us that a 1% increase in the price of salt will reduce the quantity demanded 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 (e.g., lower) than items that are non-necessities (such as restaurant meals) and items that have close substitutes (such as Chevrolets).

Table 5-1: Example Elasticities[34]

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

[34] 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 customer's EV 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 the quantity of on-peak EV charging is expected to change when the price of on-peak charging changes (all other things held constant). This is also referred to as the own-price elasticity of on-peak charging. The elasticity of off-peak EV 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 is a cross-price elasticity that shows how much the quantity of on-peak charging is expected to change when the price of off-peak charging changes; and
- ϵ_{op-p}: The elasticity of off-peak charging with respect to the price of on-peak charging, which is also a 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 due to the double subscript. These values should not be considered as second derivatives and 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.)

The elasticities are defined as applying to EV charging during the TOU time periods. However, customer decision-making probably takes place at a more granular level of time; households decide not only between charging during on-peak and off-peak periods, but also between charging from 2 to 3 PM, for example. The pricing experiment analyzed here only allowed us to model decision-making over the experimental rate's TOU time periods because those are the only time periods over which different sets of prices were observed. There are no customers in the experiment who faced different prices at 2 PM than at 3 PM, so it is not possible to make any inference about how customers responded to different prices at those times.

To estimate the elasticities listed above, a system of electricity demand equations derived from a generalized Leontief cost function were estimated. This framework treats customers as a unit or agent that consumes many inputs (e.g., electricity use) that go into the production of many *outputs*, such as labor, meals, entertainment, transportation, etc. These outputs jointly contribute to a household's utility or well-being. The focus is on one output and one input in particular: the use of an EV and the electricity used to charge it. Although it is the case that a customer's use of an EV contributes to well-being in a way that depends on many other factors in the household, there is insufficient data for each customer to model this aspect of the problem. Instead, we assume that the household's EV charging decisions are separable from its decisions to consume other goods and services. This allows us to 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 estimation procedure uses the amounts of electricity consumed to charge the EV in each of the pricing periods: on-peak, off-peak and super off-peak. A cost function is specified that includes prices, quantities and parameters that describe the total costs of EV charging associated with a given level of EV usage and estimates the parameters of the cost function using load data and the price variation across customers in the pilot. A generalized Leontief (GL) cost function is used that is essentially a special case of the model presented in Aigner, Newman and Tishler (1994),[35] who use the GL functional form to examine non-residential TOU rates in Israel. As with their model, three distinct periods of consumption are used: on-peak, off-peak and super off-peak. After estimating the parameters of the cost function, elasticities are calculated for the experimental TOU rates, which can be used to estimate impacts for other possible TOU rates.

The foundation of the model is the assumption that the customer chooses consumption during each period to minimize the cost function that contains total household production and electricity prices during different periods of the day.[36] For any given set of prices, there is an optimal amount of production (and therefore utility) that the household can achieve, and the solution to minimizing the cost function represents the lowest cost at which a customer can achieve that level of production under a given set of prices.

The GL cost function is defined such that the cost of EV charging (C) is a function of EV usage (y), prices (p_i for $i = 1,2,3$) and parameters (β_{ij} for $i, j = 1,2,3$).[37]

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

From the cost function, it is possible to derive equations that define the share of each period's expenditure (m_i) as a percentage of total expenditure in terms of prices and parameters.[38]

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

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.

35 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).

36 A detailed description of the derivation of model is included in Appendix B.

37 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.

38 Note that the model does not differentiate among days and therefore within the model there is no difference between expenditure shares at a daily level and expenditure 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.

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, the own-price elasticities were calculated using:

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

and the cross price elasticities using:

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

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

5.2 Data

The data used to estimate the model comes from 430 customers who were on an experimental EV TOU rate at some point during the Study period. In order to maximize the price variation that is used to identify the model, data for all of the rate groups and both seasons was included in the estimation. The data covers the period from January 2011 until October 2013 and originates as 15-minute or 1-hour interval measurements of kWh. The electricity rates from Table 2-1 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 expenditure respectively. Appendix B shows results for alternative choices of data as model inputs.

A good first step in analyzing Study results is to evaluate the implementation of the experimental design. In this case, a crucial part of the experiment is that customers who chose 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 using data from a survey completed during the Study that demonstrates the successful randomization of customers onto one of the three experimental TOU rates. The table shows counts of customers with 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. 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 three experimental EV TOU rates.

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

Table 5-2: Distributions of Customer Characteristics on Experimental Rates[39]

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%	

39 All customer characteristics in this report come from the survey of Study participants conducted in 2012. For more details, see "First Year Evaluation for San Diego Gas & Electric's Electric Vehicle Pilot." Prepared by Freeman, Sullivan and Co. (2012). Appendix C reports that 102 participants responded to the survey and were able to be matched to EV charging data, however 4 of these participants did not respond to the questions presented in the table, making the total customer count equal to 98.

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	
	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 3-8 through 3-12, 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

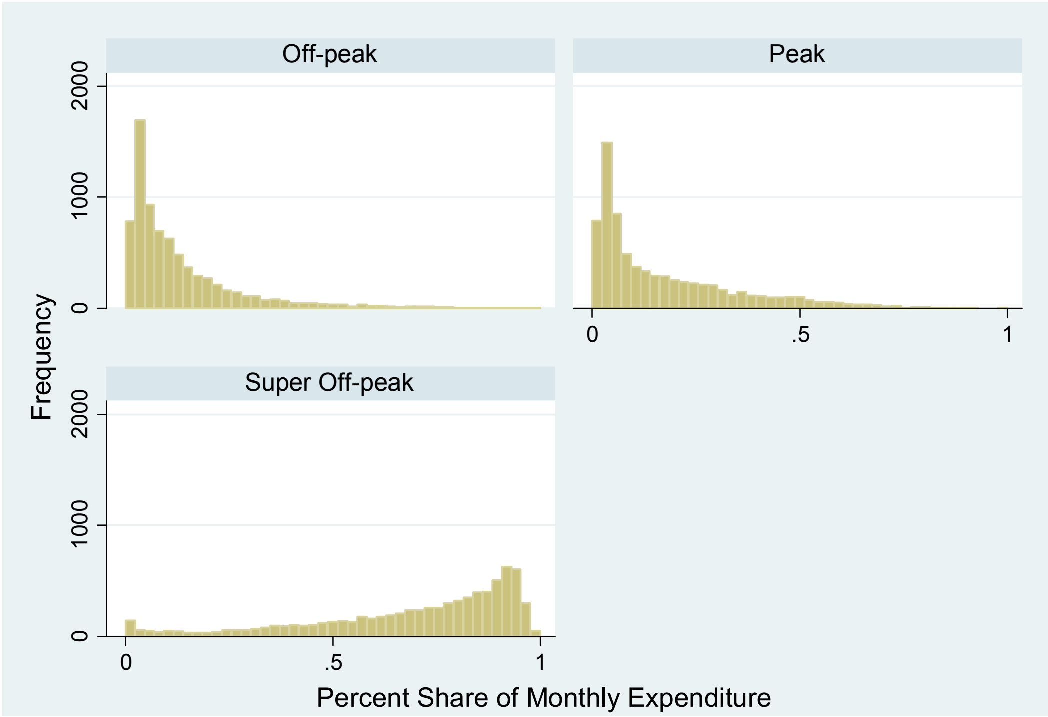
Rates	Average kW per Period			% Load per Period		
	Peak	Off-peak	Super Off-peak	Peak	Off-peak	Super Off-peak
EPEV-L	0.10	0.11	1.28	7%	7%	86%
EPEV-M	0.09	0.09	1.44	6%	6%	89%
EPEV-H	0.07	0.08	1.41	4%	5%	90%

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

Rates	Average kW by Period			% Load per Period		
	Peak	Off-peak	Super Off-peak	Peak	Off-peak	Super Off-peak
EPEV-L	0.11	0.10	1.19	8%	7%	85%
EPEV-M	0.09	0.08	1.34	6%	5%	89%
EPEV-H	0.08	0.07	1.34	5%	5%	90%

Figure 5-1 shows histograms of the shares of total EV charging expenditure in each rate period for every customer-month included in the Study. As the histograms show, the share of expense for super off-peak charging is much higher than the share of on-peak and off-peak charging due to the fact that most charging occurs during the super off-peak period.

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



During the first year of the Study (Jan 2011 – Jan 2012), a significant number of new customers enrolled each month (see Figure 2-1). 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.

5.3 Results

Intuitively, all own-price elasticities are expected to be negative, while cross-price elasticities could be either positive or negative. Negative own-price elasticities indicate that the demand for electricity falls as the price increases. For the cross-price elasticities, positive values indicate that two goods 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 the goods are complements. This means that as the price of electricity increases during one time period, the demand for electricity decreases in the other period[40].

As a check to see how well the model fits the data, the parameter estimates and prices were used to predict what the share of charging would be for each rate period under the summer prices. These predictions are compared to the actual charging shares. Table 5-5 shows the results, which indicate that the model generally over predicts the share of charging in the super off-peak period, but never by more

[40] Common examples of goods and services that are substitutes include use of driving/mass-transit, organic/conventional produce, and electricity produced by renewable sources vs. fossil-fuel sources. Examples of complements include hamburgers and hamburger buns, beach chairs/umbrellas and tennis racquets/balls.

than 6%. This indicates that the model does a good job of predicting the average monthly EV charging shares for each of the rate groups at these prices.

Table 5-5: Predicted Versus Actual Usage Shares

Day Type	Rates	Usage Shares (%)					
		Predicted			Actual		
		Peak	Off-Peak	Super Off-Peak	Peak	Off-Peak	Super Off-Peak
Weekday	EPEV-L	10%	12%	78%	11%	16%	73%
	EPEV-M	6%	8%	87%	7%	9%	84%
	EPEV-H	4%	8%	89%	6%	9%	84%
Weekend	EPEV-L	13%	11%	76%	14%	14%	72%
	EPEV-M	7%	7%	85%	11%	10%	79%
	EPEV-H	5%	8%	88%	9%	8%	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 expenditure in the on-peak period and the super off-peak period. The off-peak EV charging share is fully determined by the other two equations because the total of the expenditure shares must sum to 100%. The R^2 value of the super off-peak to on-peak period equation is 0.89 for weekdays and 0.86 for weekends, indicating a very close fit of the model to the data. The R^2 value of the on-peak period equation is 0.45 for weekdays and 0.43 for weekends, indicating a looser model fit with more unexplained variation. The model is likely predicting super off-peak period EV charging better because that is when a large fraction of EV charging occurs. On-peak period charging, on the other hand, is much rarer, more idiosyncratic and therefore more difficult to estimate accurately.

Using the parameter estimates obtained from the model, we calculated the associated elasticities for several subgroups of the experiment population. Table 5-6 shows elasticity estimates for non-PV customers for both the weekday and weekend models.[41] Note from Equation (3) that the elasticity formulas include prices, so even though the estimated cost function parameters are constant across rate groups, the elasticities themselves will vary. Two prices are required to estimate the elasticities and so the table reports elasticities using the appropriate period prices for each experimental rate. Thus, the table should be interpreted as having three estimates of each price elasticity (one from each rate) on both weekdays and weekends. Although standard errors are not shown, all of the elasticity estimates are significantly different from zero at a 99% confidence level.

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

Table 5-6: Elasticity Results by Day Type for Non-PV Customers[42]

Type of Price Elasticity	Elasticity	Day Type					
		Weekday			Weekend		
		EPEV-L	EPEV-M	EPEV-H	EPEV-L	EPEV-M	EPEV-H
Own	ϵ_{p-p}	-0.42	-0.38	-0.36	-0.47	-0.46	-0.45
	ϵ_{op-op}	-0.45	-0.42	-0.41	-0.46	-0.45	-0.44
	$\epsilon_{sop-sop}$	-0.23	-0.27	-0.28	-0.26	-0.30	-0.31
Cross	ϵ_{p-op}	-0.19	-0.27	-0.25	-0.12	-0.17	-0.16
	ϵ_{op-p}	-0.17	-0.28	-0.40	-0.14	-0.23	-0.32
	ϵ_{p-sop}	0.61	0.65	0.60	0.60	0.63	0.62
	ϵ_{sop-p}	0.11	0.13	0.15	0.14	0.17	0.19
	ϵ_{op-sop}	0.61	0.69	0.80	0.60	0.67	0.76
	ϵ_{sop-op}	0.12	0.14	0.13	0.12	0.13	0.12

Note: All estimates are statistically significant at a 99% confidence level.

The own-price elasticities are all negative, as expected; because an increase in the price of charging during a given period should cause a decrease in demand during that period. Despite the fact that the EV charging load shapes are quite different from those associated with a typical whole house residential TOU rate, the estimated own-price elasticities for EV charging are similar to other types of residential load. The elasticities for the on-peak period and off-peak period are higher than that for the super off-peak period, but all three elasticities fall in the range of results found during the California Statewide Pricing Pilot, where daily own-price elasticities for residential customers were estimated to be between negative 0.3-0.5.[43] The lower own-price elasticity estimates for the super off-peak period are likely due to a combination of charging timers making it relatively easy for EV charging during that period, customer schedules that limit long charging events to the off-peak or super-off peak periods and the fact that the average length of a charging period fits fully within the super-off peak time period.

Not all of the cross-price elasticities are positive, which is somewhat surprising, but not entirely implausible. It is generally expected that electricity usage between any two periods would be substitutes, but Table 5-8 suggests that electricity usage between the on-peak and off-peak periods are partially complementary because ϵ_{p-op} and ϵ_{op-p} are negative across all price schedules. This implies that all else being equal, an increase in the off-peak period price causes a decrease in the usage of

42 The elasticities presented here differ significantly from the estimates contained in the interim report for this project (see "First Year Evaluation for San Diego Gas & Electric's Electric Vehicle Pilot." Prepared by Freeman, Sullivan and Co., (2012)). In the prior report, the share equations were incorrectly specified in terms of kWh usage rather than expenditure shares. This significantly overstated the price elasticities. The estimates presented here are based on the same theoretical framework as the prior analysis, but here the framework was properly applied, whereas previously it was not.

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

electricity in the on-peak period and vice versa. Such a result suggests that many customers may not differentiate between the on-peak and off-peak periods in their EV charging decisions. A simple rule a customer might use to decide when to charge that could lead to this pattern would be, "use the charging timer to charge overnight as much as possible, and then charge at other times as necessary."

Elasticities can also be calculated for different seasons as well as for PV owners. Results for these subgroups of the Study population are shown in Table 5-7 and Table 5-8, respectively. As seen in Table 5-7, there is very little variation in elasticities across seasons.

Table 5-7: Elasticity Results by Season for Non-PV Owners

Day Type	Type of Price Elasticity	Elasticity	Rates					
			Summer			Winter		
			EPEV-L	EPEV-M	EPEV-H	EPEV-L	EPEV-M	EPEV-H
Weekday	Own	ϵ_{p-p}	-0.41	-0.37	-0.35	-0.43	-0.38	-0.36
		ϵ_{op-op}	-0.44	-0.41	-0.40	-0.45	-0.42	-0.41
		$\epsilon_{sop-sop}$	-0.23	-0.27	-0.29	-0.22	-0.26	-0.28
	Cross	ϵ_{p-op}	-0.19	-0.29	-0.26	-0.19	-0.26	-0.24
		ϵ_{op-p}	-0.19	-0.30	-0.43	-0.14	-0.25	-0.37
		ϵ_{p-sop}	0.60	0.66	0.61	0.62	0.64	0.60
		ϵ_{sop-p}	0.11	0.13	0.16	0.10	0.13	0.15
		ϵ_{op-sop}	0.64	0.71	0.83	0.59	0.68	0.78
		ϵ_{sop-op}	0.12	0.14	0.13	0.12	0.14	0.13
Weekend	Own	ϵ_{p-p}	-0.47	-0.46	-0.45	-0.48	-0.46	-0.46
		ϵ_{op-op}	-0.46	-0.44	-0.43	-0.46	-0.45	-0.44
		$\epsilon_{sop-sop}$	-0.26	-0.31	-0.32	-0.25	-0.29	-0.31
	Cross	ϵ_{p-op}	-0.12	-0.18	-0.17	-0.12	-0.16	-0.16
		ϵ_{op-p}	-0.16	-0.25	-0.34	-0.12	-0.21	-0.30
		ϵ_{p-sop}	0.59	0.64	0.62	0.60	0.63	0.61
		ϵ_{sop-p}	0.15	0.17	0.20	0.13	0.16	0.19
		ϵ_{op-sop}	0.62	0.69	0.78	0.58	0.66	0.74
		ϵ_{sop-op}	0.12	0.14	0.12	0.12	0.13	0.12

Note: All estimates significant at a 99% confidence level.

Table 5-8 shows the price elasticities for PV owners. Although the average load shapes for the two groups are very similar, there are several differences with respect to how the two groups respond to prices. PV owners have lower own-price elasticities across the board and the own-price elasticity for off-peak prices is no longer significantly different from zero. Examining the cross-price elasticities, consumers respond to changes in super off-peak prices by shifting EV charging to the on-peak period on weekdays and to both the on-peak and off-peak periods on weekends. Off-peak prices seem to have little bearing on EV charging behavior for PV customers. There are very few differences in the estimated elasticities across seasons, which is not surprising based on the seasonal load profiles shown in Section 3.

Table 5-8: Elasticity Results by Day Type for PV Owners

Type of Price Elasticity	Elasticity	Day Type					
		Weekday			Weekend		
		EPEV-L	EPEV-M	EPEV-H	EPEV-L	EPEV-M	EPEV-H
Own	ϵ_{p-p}	-0.29	-0.23	-0.20	-0.39	-0.36	-0.33
	ϵ_{op-op}	0.12	0.16	0.23	-0.31	-0.27	-0.27
	$\epsilon_{sop-sop}$	-0.06	-0.08	-0.10	-0.10	-0.13	-0.15
Cross	ϵ_{p-op}	-0.15	-0.19	-0.16	-0.02	-0.03	-0.02
	ϵ_{op-p}	-0.17	-0.20	-0.29	-0.03	-0.04	-0.05
	ϵ_{p-sop}	0.45	0.41	0.36	0.41	0.38	0.36
	ϵ_{sop-p}	0.06	0.08	0.09	0.06	0.09	0.10
	ϵ_{op-sop}	0.05	0.04	0.04	0.34	0.31	0.32
	ϵ_{sop-op}	0.01	0.01	0.01	0.04	0.05	0.04

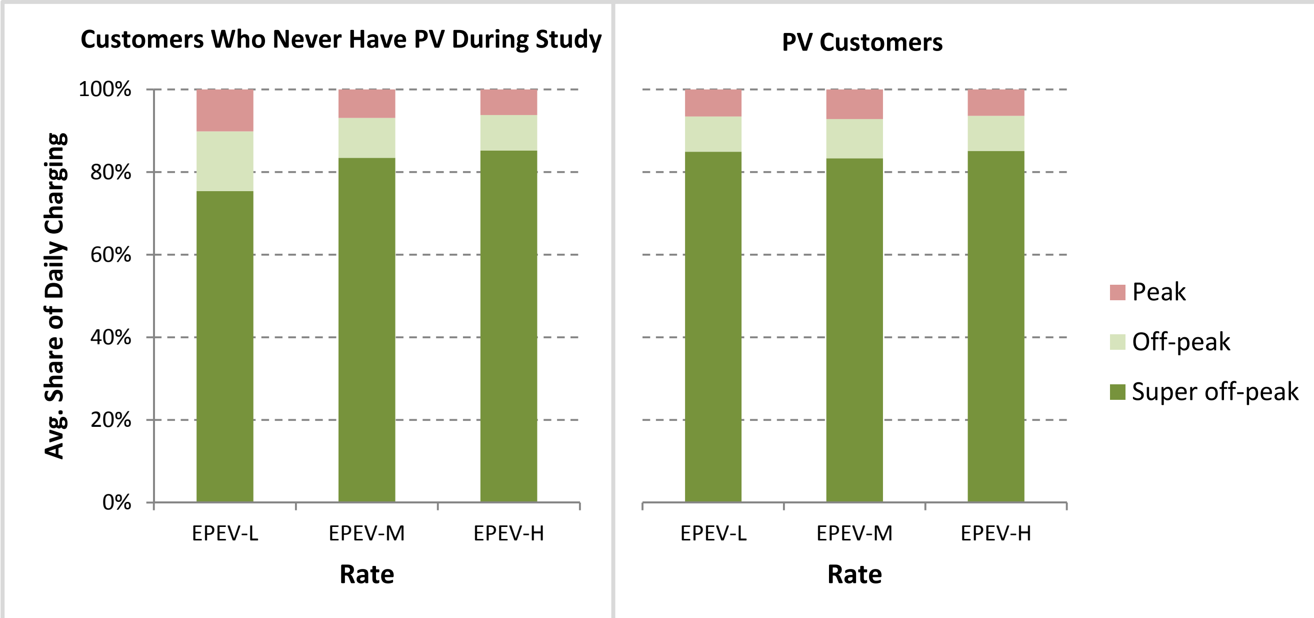
= Significant at a 99% confidence level

= Significant at a 95% confidence level

= Not significant at a 95% confidence level

Though only minor differences in price responsiveness exist between day types and seasons, PV customers are less price sensitive than non-PV customers in each of the pricing periods. One possible explanation for this is that selling PV electricity back to the grid is valued more highly than using it to charge an EV, thus further constraining the times that are available for EV charging. Another possibility is that PV owners have certain characteristics that cause them to place an even higher premium on charging overnight regardless of the prices they face (e.g., the results show a selection effect). Characteristics that would fit this hypothesis include PV customers being relatively wealthier so that they are less concerned with the price during different periods, having stronger environmental preferences that lead to a stronger preference for overnight charging or a having stronger preferences for automating their charging by using the timers. Some supporting evidence for this reasoning can be found by looking at the average share of charging by rate period for the different rate groups split out by customers who install a PV system at some point in the Study (either before or after acquiring an EV) and customers who never install a PV system. Figure 5-2 shows that the share of total charging by rate period varies across the three experimental rates for non-PV owners but is largely constant for PV owners.

Figure 5-2: Histograms of Percent Shares of Monthly Usage



5.4 Implications for EV Rate Design

There are several insights that result from a direct interpretation of the elasticities. Referring back to Table 5-6, it is revealed that for non-PV owners, super off-peak prices appear to be the most important factor influencing an EV driver's charging time decisions and behavior. Reductions in price during this period will cause more charging during the super off-peak period (negative own-price elasticity), as well as a shift in charging from the on-peak and off-peak periods to the super off-peak period (positive cross-price elasticities). As the TOU price ratios increase, so too does the cross-price elasticity between the off-peak and super off-peak period. This result indicates that for higher price ratios, reductions in the super off-peak price will result in customers switching more of their EV charging from the off-peak period to the super off-peak period. Furthermore, as the TOU price ratios increase, the magnitudes of the cross-price elasticities related to the off-peak period also increase, suggesting that the off-peak price becomes increasingly important as the difference between on-peak and super off-peak prices becomes wider.

Perhaps the most useful feature of a structural model is the ability to predict what usage behavior would look like under alternative price schedules for the same population. Because the model produces estimates of demand functions, it is possible to input different hypothetical prices into those demand functions to see how the share distributions vary. Table 5-9 shows the predicted shares of usage for various TOU rates under the assumption that the total amount of charging does not change. For example, it is now possible to compare the impact of a very high price ratio rate of 1:2:13 with the EPEV-H summer rate, which has a price ratio of 1:2.3:6.

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	6	9	87
1:2.3:6	4	6	90
1:3:8	3	5	92
1:2:13	3	4	94

The predicted results indicate how customers would respond to various price incentives (of lower rates) for EV charging during super off-peak hours. Table 5-10 shows the estimated average usage values in kWh for each rate period under the alternative scenarios analyzed in Table 5-9. As the ratio of on-peak to super off-peak prices increases, consumers shift more EV charging onto super off-peak hours and charge less during on-peak and off-peak hours. Under the most extreme rate scenario, with an on-peak to super off-peak ratio of 1:13, the on-peak EV charging falls to about 3% of total usage.

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

Price Ratio	Peak	Off-peak	Super Off-peak
1:2:3	0.49	0.69	6.82
1:2.3:6	0.33	0.49	7.18
1:3:8	0.26	0.36	7.37
1:2:13	0.24	0.28	7.48

The results provide an additional insight for PV customers. Besides being less price sensitive to EV charging rates in general, PV customers are particularly unresponsive to prices in the off-peak period. This insight suggests that a two-period TOU rate may be just as effective in encouraging off-peak charging as a three-period rate for PV customers.

Caution should be used when attempting to compare Study results with residential increasing block rates. 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 daily TOU time periods. Customers participating in this experiment were not subject to increasing block rates for their EV charging, so there is no way to use the data in this experiment to develop a model that accounts for behavior under a TOU rate and an increasing block rates.

6 Conclusions

This report documents results from San Diego Gas & Electric Company's (SDG&E's) multi-year plug-in EV Pricing and Technology Study, which used an innovative research design to randomly assign EV customers to one of three temporary experimental rates for EV usage, billed separately from the rest of their premises usage. Each experimental rate had varying price differences between on-peak, off-peak and super off-peak prices. This Study provides a relevant and timely perspective of EV customer response to time-varying rates for EV charging, to inform CPUC rate policy.

The key findings of the report are:

- Most EV charging takes place during the super off-peak period aided by charging timers;
- EV customers exhibit learning behavior;
- EV charging behavior responds to price signals; and
- EV customers are most responsive to changes in on-peak and off-peak prices.

Customers in the rate experiment began the vast majority of their EV charging events during early super off-peak hours (between 12 AM and 2 AM) and charged their vehicles less frequently on weekends. An average charging event lasted for about three hours and owners generally charged their vehicles only once per day. Enabling technology in the form of timers appear to be heavily used by a majority of EV customers and there is some evidence that customers facing stronger price signals are more likely to adhere to a fixed EV charging schedule.

EV charging patterns do not vary between seasons and on average, there is no difference in charging loads between PV customers and non-PV customers in the experimental TOU rate groups. EV charging behavior is very similar between customers on the TOU rates with strong price signals (EPEV-M and EPEV-H), but customers facing the weakest price signals (EPEV-L) charge relatively more outside of the super off-peak period. This suggests that the degree to which customers respond to the TOU rate depends on the price signal strength (on-peak to off-peak price ratio) up to a point, after which further increases in the price ratio have a minimal impact on charging behavior.

There is also evidence that EV customers exhibit learning behavior. During the first four months of Study enrollment, consumers in all three experimental rate groups (particularly those on the EPEV-L and EPEV-M rates) increased their share of super off-peak charging and decreased their share of on-peak charging. During this learning phase, the share of super off-peak charging for EPEV-L and EPEV-M customers increased by 1.8-2.9% per month and the share of on-peak charging decreased by 0-1.3% per month compared to the rest of the Study period. This pattern occurs both on weekdays and weekends and could be explained by some form of learning about the charging timer technology as well as learning about the cost impact of by charging during various TOU periods through the monthly bill. Super off-peak charging shares stay relatively stable after this initial upward trend, while on-peak charging shares gradually increase over the remainder of the Study period.

Elasticity estimates from the structural demand model show that the responsiveness of non-PV customers to changes in the price of electricity used for EV charging is similar to observed price responses for residential household consumption from prior estimates (own price elasticities in the range of negative 0.3-0.5). PV customers, however, are much less price sensitive in all rate periods despite their similar load shapes and appear to not be influenced by the price in the off-peak period. Simulations of EV charging behavior under TOU rates with other price ratios suggest that a mild price differential between the super off-peak and on-peak periods results in consumers using 80-90% of their electricity for EV charging during the super off-peak period, with further increases in the price ratio having diminishing impacts.

This Study provides insight on EV customers' response to time-varying rates for EV charging and constitutes valuable information that can inform rate-setting policy at the CPUC as well as other jurisdictions. However, the results presented in this report must be viewed in the proper context – all data analyzed here represent the behavior and choices of customers who are early adopters of a new technology – in this case, an all-electric EV. Their behavior can reasonably be expected to be similar to EV customers in the near future, but may not be representative of a future population of customers who may eventually adopt EVs years from now. Nonetheless, the analysis contained in this report is an important and necessary starting point and provides heretofore non-existent information about trends and outcomes in the early stage of EV technology adoption.

Appendix A Nissan LEAF Features & EV Project Background

A.1 Nissan LEAF Features

- Five Passenger Hatchback
- EPA average 73 mile range when fully charged[44]
- 100% Electric - Zero Emission Vehicle
- Accepts Level 1, Level 2 and DC Fast Charging
- Lithium Ion Battery (24kWh capacity)
- About 7 hours for full charge – Level 2 (240v, 3.3 kW charge power)
- < 30 min to go to 80% SOC on DC Fast Charge
- Recycled materials for interior and other components
- Displays SOC in "distance to empty," GIS Map of area reachable
- Has on-board charging time and duration settings and remote applications

A.2 EV Project Background

This project was an ECOtality, U.S. DOE and Nissan collaboration to carry out the largest deployment of EVs and charging infrastructure in U.S. history under the U. S. Department of Energy's National Energy and Technology Laboratory Recovery Act (Transportation Electrification Funding Opportunity Number: DE-FOA-0000028)[45]. The following cities make up the scope of participation as originally announced, which was subsequently expanded during 2010: San Diego, Seattle, Portland/Salem, Phoenix/Tucson and Nashville/Knoxville/Chattanooga.

$200 million in project funding was secured to deploy charging infrastructures in the U.S. -- $100 million of which was ARRA. An additional $8 million grant from CEC to eTec was awarded for installing additional infrastructure. Infrastructure planned for the San Diego region was as follows:

- 925 "Free Allowance" Level 2 (220V) charging units – Blink Residential Charging Installations
- About 500 Level 2 (220V) charging units at about 130 locations – Public and Commercial Chargers (majority deployed late 2012 through mid-2013)
- 6 DC (480V) "Fast Chargers" (deployed late 2012 through mid-2013)

A.3 Photos of EV Charging and Metering Equipment

The following photos show the Level 2 EV charging unit (see Figure A.3-1) and metering equipment (See Figure A.3-2) that was installed at each customer's home as a part of the EV Project and SDG&E's EV Pricing and Technology Study, respectively.

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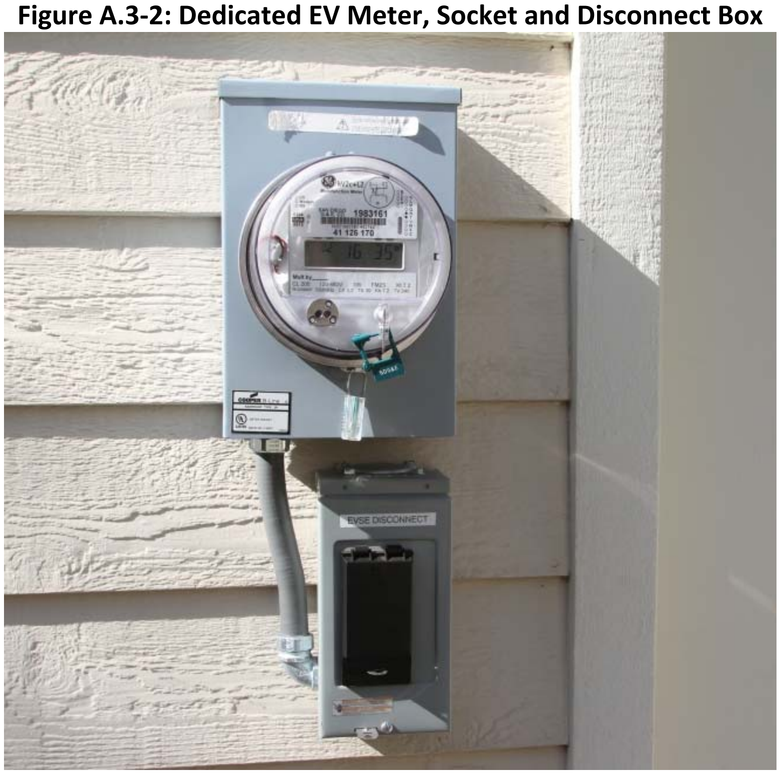
44 Source http://www.pluginamerica.org/sites/default/files/imagecache/image_full/vehicle-images/nissan_leaf_3.jpg

45 See http://energyindependence.wi.gov/docview.asp?docid=16303&locid=160 for more details.

Figure A.3-1: Level 2 EV Charging Unit

Figure A.3-2: Dedicated EV Meter, Socket and Disconnect Box



Appendix B Model Development

This appendix provides a more technical description how the electricity demand model was specified and estimated.

B.1 Model

In this report, the energy usage for EV Charging was modeled using a generalized Leontief (GL) cost function. The model used was essentially a special case of the model presented in Aigner, Newman and Tishler (1994), who examined non-residential TOU rates in Israel. This report used the case of the model with three-period pricing: peak, off-peak and super off-peak.

The GL cost function (derived from a GL production function) was introduced by Diewert (1971)[46] to obtain input demand equations that are linear in technological parameters for the purposes of facilitating econometric estimation. The GL function was an appealing choice 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.[47] 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)[48] claim that the GL specification offers improved flexibility because it imposes relatively few restrictions on the substitution possibilities. This feature allows the experimental design (having three distinct TOU rates for each of the three time periods) to be fully utilized while estimating own-price elasticities and cross-price elasticities between all of the time periods. Other models, like the translog model used in Chung and Aigner (1981)[49] are incapable of testing the hypothesis of zero substitutability between periods.[50]

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.

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

47 Tishler, A. and S. Lipovetsky, “The Flexible CES-GBC Family of Cost Functions: Derivation and Application”, Review of Economics and Statistics. (1997).

48 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).

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

50 Woo, C. “Demand for Electricity of Small Nonresidential Customers under Time-Of-Use (TOU) Pricing.” The Energy Journal. (1985).

The model used one-hour interval data that measures EV charging usage. The data was aggregated such that dependent variables are the monthly average shares of on-peak, off-peak, and super off-peak, weekday EV charging. Therefore, the shares represent each pricing period's fraction of the total monthly expenditure on energy consumed for EV charging. Share models were used as a way of normalizing EV charging loads so that relative usage within a given pricing period could 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:

$$y = \sum_{i=1}^{3} \sum_{j=1}^{3} \alpha_{ij} \left(x_i x_j\right)^{1/2} \qquad \text{(B-1a)}$$

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 EV charging consumption at different times of day.

Given equation (B-1a), Nexant assumed 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,

$$\min \sum_{i=1}^{3} x_i p_i \qquad \text{(B-1b)}$$

subject to the constraint

$$y = \sum_{i=1}^{3} \sum_{j=1}^{3} \alpha_{ij} \left(x_i x_j\right)^{1/2} \qquad \text{(B-1c)}$$

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

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

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 yields the demand for each input i:

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

The resulting share equations are:

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

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 (B-4), the *k* and *j* indices each go from 1 to 3. Dividing the top and the bottom of equation (B-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 (B-3) with respect to the prices, the own-price and cross-price elasticities then respectively become:

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

and

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

B.2 Estimation

Classical additive disturbances $(u\ )$ are added to the model for each of the share equations (B-4), which result in equations (B-8) below. Aggregated one-hour data was used to estimate the monthly expenditure share equations (B-4) subject to the constraints (B-6), (B-7a) and (B-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 (B-5), subject to the constraints (B-6), (B-7a) and (B-7b) were then estimated using nonlinear seemingly unrelated regressions (SUR).

This results in the system:

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

where

$$\beta_{ij} = \beta_{ij}^{0} + W\beta_{ij}^{1} \text{ for i, j} = 1{,}2{,}3 \tag{B-9a}$$

$$\beta_{33}^{1} = \sum_{i}\sum_{j}\beta_{ij}^{1}\, for\ i,j \neq 3{,}3 \tag{B-9b}$$

and

$$\beta_{33}^{0} = \frac{1}{2} - \sum_{i}\sum_{j}\beta_{ij}^{0}\, for\ i,j \neq 3{,}3 \tag{B-9c}$$

The estimation of the SUR model was done in STATA, using the *nlsur* function, which fits a system of nonlinear equations by feasible generalized nonlinear least squares (FGNLS). FGNLS was used because the error variance matrix is unknown, but can be estimated in the first stage of the estimation (see (B-11) below). This procedure corrects for the autocorrelation that is likely to exist in the observations for each individual owner.

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 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:

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

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 j^{th} observation.

The FGNLS estimation procedure is essentially a two stage process. In the first step the NLS regression was run assuming $\delta = I\ (identity\ matrix)$ in (B-10). This provided a consistent estimate of $\hat{\beta}_{NLS}$, which was then used to estimate δ as follows:

$$\hat{\delta} = \sum_{i=1}^{N} \frac{1}{N} \hat{u_i}' \ \hat{u_i} \qquad \text{(B-11)}$$

where

$$\hat{u_i} = m - g(x_i, \hat{\beta}_{NLS}) \qquad \text{(B-12)}$$

$\hat{\delta}$ was then plugged into (B-10) for δ which gives a new and final estimate of β, $\hat{\beta}_{FGNLS}$.

Table B-1 presents the estimates of the *β* coefficients in the model for non-PV owners. Separate models were estimated for weekdays and weekends, and the table shows sets of parameters for each. The reason for this separate weekday and weekend modeling is a household's decisions about charging might be expected to be quite different on weekends than 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, but two of them (β_{13} and β_{33}) are different at an 90% confidence level, which is more than 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. Recall, these parameters are estimated pieces of the cost function, they are not elasticity estimates. However, with these estimates Nexant can derive the own-price elasticities and cross-price elasticities for each period.

Table B-1: Model Coefficient Estimates

Weekend/ Weekday	Parameter	Coefficient	Std. Err.	95% Confidence Interval	
Weekday	β_{11}	0.007**	0.002	0.003	0.010
	β_{12}	-0.019**	0.003	-0.025	-0.013
	β_{13}	0.066**	0.004	0.058	0.075
	β_{22}	0.007	0.007	-0.007	0.021
	β_{23}	0.087**	0.007	0.074	0.100
	β_{33}	0.217**	0.011	0.196	0.238
Weekend	β_{11}	0.003	0.002	-0.002	0.008
	β_{12}	-0.015**	0.003	-0.022	-0.009
	β_{13}	0.084**	0.005	0.074	0.095
	β_{22}	0.006	0.008	-0.010	0.022
	β_{23}	0.083**	0.007	0.069	0.098
	β_{33}	0.187**	0.012	0.164	0.210

Significance Codes: *=5%, **=1%

Appendix C Linking EV Charging Behavior to Survey Responses

This section presents findings on survey responses associated with EV 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.[51] Since that analysis took place, however, survey responses can now be linked to EV 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 EV 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 C-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.

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

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

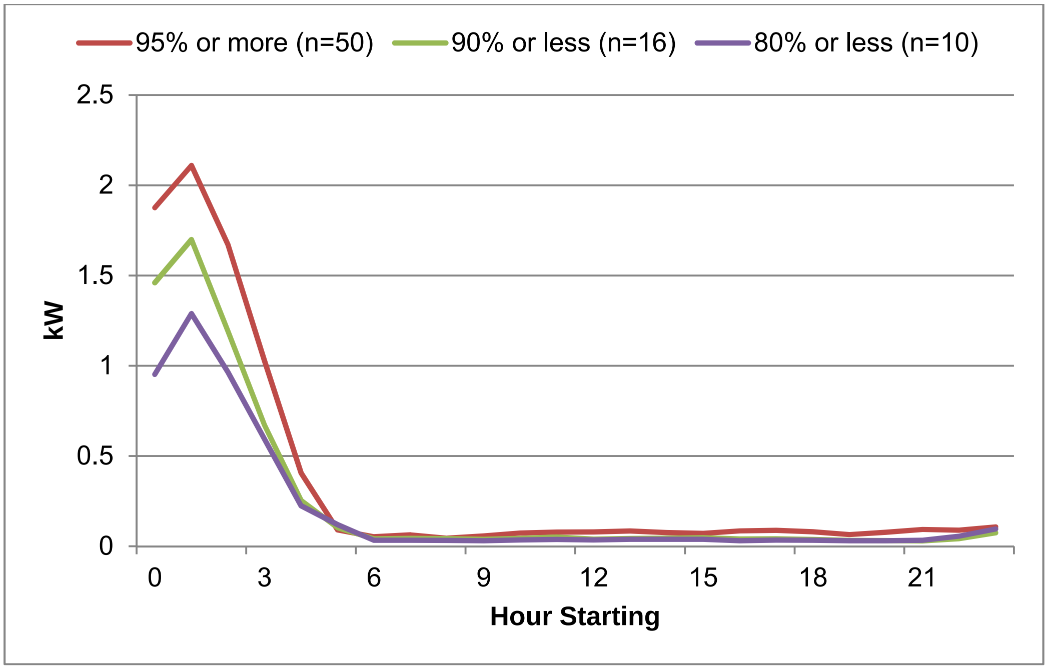


Table C-1 shows average demand categorized by the percentage of home charging activity and TOU period. The basic pattern shown in Figure C-1 arises here as well. Customers with lower proportions of at-home charging have lower levels of off-peak and peak charging as well as super off-peak charging.

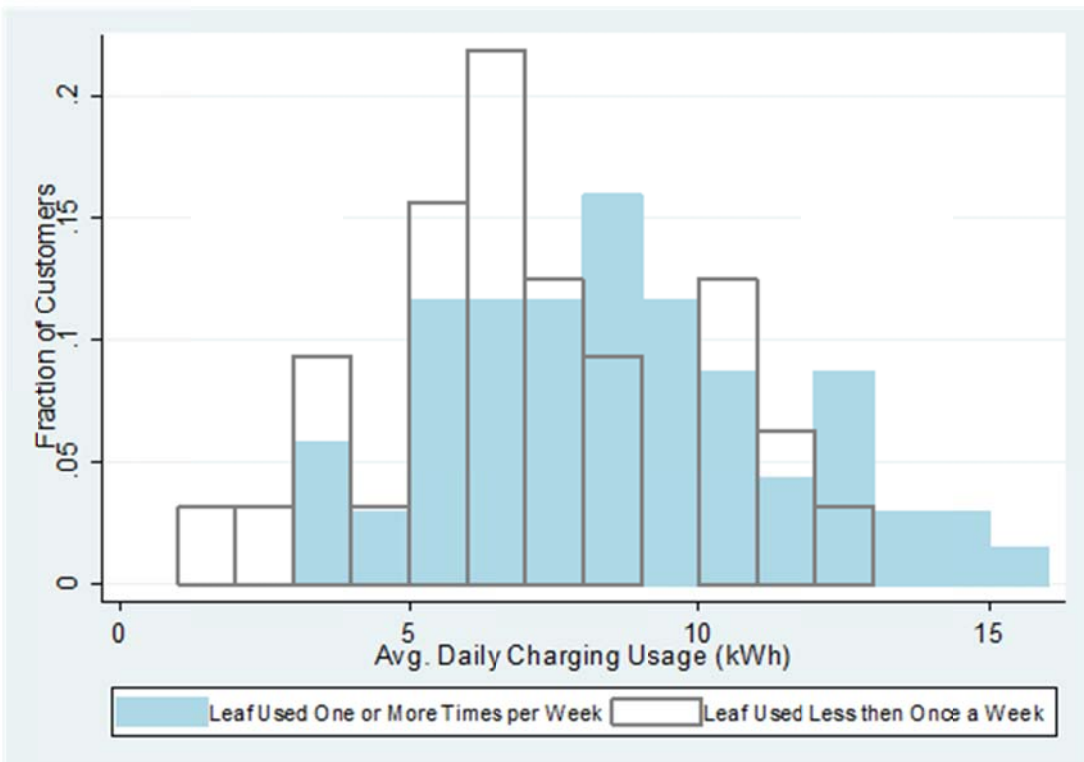
Table C-1: Average Survey Participant TOU Period Demand (kW) by Percent of Charging Activity at Home

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 charging timer on their EV. The customers who used the timer were asked the start and end times during which they set the timer. The interval data of the 89 survey participants who indicated that they used the timer was examined to determine if most of their charging activity took place during the time period set by the participants. Based on EV 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 Nissan LEAF for driving to work or school, short trips around town, vacations, long trips, business or work use. Participants were categorized 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 C-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 C-2.

Figure C-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 C-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. The maximum of those hourly averages for each customer was taken and called 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 C-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

Demographic Characteristic	Avg. Daily Usage (kWh)	Maximum Demand on the Average Day (kW)	Number of Customers
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 C-3 through C-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 C-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 C-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 C-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 EV 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 EV charging timer, in conjunction with the TOU pricing, is sufficient to strongly influence EV charging patterns despite major differences in customer characteristics.