2020 Load Impact Evaluation of San Diego Gas and Electric's Electric Vehicle Rates

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Michael Ty Clark
Daniel G. Hansen

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Christensen Associates Energy Consulting, LLC
800 University Bay Drive, Suite 400
Madison, WI 53705-2299

Voice 608.231.2266 Fax 608.231.2108

Table of Contents

Abstract **1**
Executive Summary **2**
ES.1 Resources Covered 2
ES.2 Evaluation Methodologies 2
ES.3 Ex-Post Load Impacts 3
ES.3.1 TOU peak load impacts – EVTOU2 to EVTOU5 3
ES.3.2 TOU peak load impacts – Standard Tiered Rate to EVTOU2 4
ES.3.3 TOU peak load impacts – Standard Tiered Rate to EVTOU5 5
ES.3.4 VGI Pilot Evaluation Study Findings 7
ES.4 Ex-Ante Load Impacts 7
ES.4.1 Enrollment forecast 7
ES.4.2 *Ex-Ante* load impacts –EVTOU2 8
ES.4.3 *Ex-Ante* load impacts –EVTOU5 9
1. Introduction and Purpose of the Study **11**
2. Description of Rates **11**
3. *Ex-Post* Evaluation Methodology **13**
3.1 Data 13
3.2 Analysis Methods 13
3.2.1 Evaluation design and control group matching 13
3.2.2 Fixed-effects panel regression models 15
3.2.3 *Ex-post* models for estimating TOU load impacts 15
3.2.4 Calculating uncertainty-adjusted load impacts 17
3.2.5 Validity assessment 18
3.3 Further Methods for EVTOU Analyses 18
3.3.1 Transition from EVTOU2 to EVTOU5 Analysis 18
3.3.2 Incremental EVTOU2 and EVTOU5 Analysis 19
3.4 VGI Pilot Evaluation Methods 21
4. EVTOU *Ex-Post* Load Impact Study Findings **23**
4.1 TOU control group matching results for EVTOU2 to EVTOU5 customers 23
4.2 Ex-post TOU load impacts for EVTOU2 to EVTOU5 customers 24
4.3 Ex-post TOU load impacts for EVTOU2 customers 27
4.4 Ex-post TOU load impacts for EVTOU5 customers 31
5. VGI Pilot Evaluation Study Findings **34**
6. *Ex-Ante* Evaluation Methodology **41**
6.1 Per-customer load impacts 42
6.2 Per-customer reference loads 42
6.3 Enrollment forecast 43
6.4 COVID-19 Adjustments to the Ex-Ante Forecast 44
7. EVTOU *Ex-Ante* Load Impact Study Findings **48**
7.1 Ex-Ante TOU load impacts for EVTOU2 customers 48
7.2 Ex-Ante TOU load impacts for EVTOU5 customers 51

8. Comparisons of Results 53
8.1 EVTOU2 53
8.1.1 Previous versus current *ex-post* 53
8.1.2 Previous versus current *ex-ante* 53
8.1.3 Previous *ex-ante* versus current *ex-post* 54
8.1.4 Current *ex-post* versus current *ex-ante* 55
8.2 EVTOU5 56
8.2.1 Previous versus current *ex-post* 56
8.2.2 Previous versus current *ex-ante* 57
8.2.3 Previous *ex-ante* versus current *ex-post* 58
8.2.4 Current *ex-post* versus current *ex-ante* 59
9. Recommendations 60
Appendices 61
Appendix C: EVTOU Customer Structural Breaks 61

List of Tables

Table ES.1: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Month* 3
Table ES.2: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Season & Climate Zone* 4
Table ES.3: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Month* 5
Table ES.4: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Season & Climate Zone* 5
Table ES.5 TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Month* 6
Table ES.6: TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Season & Climate Zone* 7
Table 3.1: Description of Variables Used in the EVTOU Analysis Regressions 17
Table 3.2: Description of Variables Used in the Identification of Electric Vehicle Adoption Regressions 20
Table 3.3 Description of Variables Used in the VGI Evaluation Regressions 22
Table 4.1: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Month* 25
Table 4.2: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Season & Climate Zone* 25
Table 4.3: TOU Average *Daily* Load Impacts for EVTOU2 to EVTOU5 Customers, *by Month* 26
Table 4.4: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Month* 28
Table 4.5: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Season & Climate Zone* 29
Table 4.6: TOU Average *Daily* Load Impacts for EVTOU2 Customers, *by Month* 29
Table 4.7: TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Month* 31
Table 4.8: TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Season & Climate Zone* 32
Table 4.9: TOU Average *Daily* Load Impacts for EVTOU5 Customers, *by Month* 32
Table 5.1 VGI Pilot Summary Statistics 35
Table 5.2: VGI Regression Results 41
Table 6.1: Descriptions of Terms included in the COVID Regression Equation 45
Table 8.1: Comparison of Previous and Current *Ex-Post* EVTOU2 Load Impacts 53
Table 8.2: Comparison of Previous and Current *Ex-Ante* EVTOU2 Load Impacts 54
Table 8.3: Comparison of Previous *Ex-Ante* and Current *Ex-Post* EVTOU2 Load Impacts 55
Table 8.4: Comparison of Current *Ex-Post* and *Ex-Ante* EVTOU2 Load Impacts 56
Table 8.5: Comparison of Previous and Current *Ex-Post* EVTOU5 Load Impacts 57
Table 8.6: Comparison of Previous and Current *Ex-Ante* EVTOU5 Load Impacts 58

Table 8.7: Comparison of Previous *Ex-Ante* and Current *Ex-Post* EVTOU5 Load Impacts 59
Table 8.8: Comparison of Current *Ex-Post* and *Ex-Ante* EVTOU5 Load Impacts 60
Table C.1: Count of Incremental EV Customers Based on Structural Breaks 62

List of Figures

Figure ES.1: Enrollments in EVTOU Rates 8
Figure ES.2: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 9
Figure ES.3: Aggregate TOU Load Impacts (MWh/h) – *EVTOU5* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 10
Figure 2.1: EV Rate Time-of-Use Periods and Prices 12
Figure 4.1: EVTOU2 to EVTOU5 and Matched Control Group Load Profiles – *Summer*... 23
Figure 4.2: EVTOU2 to EVTOU5 and Matched Control Group Load Profiles – *Winter*..... 24
Figure 4.3: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, August 2020*)..... 27
Figure 4.4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, January 2020*)..... 27
Figure 4.5: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 Customers (*Average Weekday, August 2020*) 30
Figure 4.6: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 Customers (*Average Weekday, January 2020*)..... 30
Figure 4.7: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, August 2020*) 33
Figure 4.8: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, January 2020*)..... 34
Figure 5.1: Aggregate VGI Energy Consumed Over Time 36
Figure 5.2: Unique VGI Driver Counts Over Time 36
Figure 5.3: Distribution of VGI Pilot Charging Start Hours 37
Figure 5.4: Distribution of VGI Pilot Session Total Duration..... 37
Figure 5.5: August 2020 Low vs High Price Days, Home: RTD 38
Figure 5.6: August 2020 Low vs High Price Days, Work: RTD 39
Figure 5.7: August 2020 Low vs High Price Days, Work: RTH 39
Figure 6.1: Enrollments in EVTOU Rates..... 44
Figure 6.2: *Ex-Ante* August Load with Covid-19 Adjustment, EVTOU2 non-NEM Customers 46
Figure 6.3: *Ex-Ante* August Load with Covid-19 Adjustment, EVTOU2 NEM Customers 46
Figure 6.4: *Ex-Ante* Aggregate June Load with Covid-19 Adjustment, EVTOU5 non-NEM Customers 47
Figure 6.5: *Ex-Ante* Aggregate June Load with Covid-19 Adjustment, EVTOU5 non-NEM Customers 47
Figure 6.6: COVID-19 Transition Path Assumption..... 48
Figure 7.1: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU2 Customers,* (*August 2022 SDG&E 1-in-2 Average Weekday*)..... 49
Figure 7.2: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU2 Customers,* (*2022 SDG&E 1-in-2 Average Weekday,* RA Window) 50

Figure 7.3: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 50
Figure 7.4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU5 Customers,* (*August 2022 SDG&E 1-in-2 Average Weekday*)..... 51
Figure 7.5: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU5 Customers,* (*2022 SDG&E 1-in-2 Average Weekday,* RA Window)..... 52
Figure 7.6: Aggregate TOU Load Impacts (MWh/h) – *EVTOU5* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 52
Figure C.1: Structural Break Example 61
Figure C.2: *Ex-post* Load Impacts for Non-NEM Incremental EVTOU2 Customers 63
Figure C.3: *Ex-post* Load Impacts for Non-NEM Incremental EVTOU5 Customers 63

Abstract

This report documents *ex-post* and *ex-ante* load impact evaluations for San Diego Gas and Electric Company's ("SDG&E") voluntary electric vehicle (EV) TOU rates, EVTOU2 and EVTOU5. Additionally, an analysis of SDG&E's vehicle grid integration (VGI) pilot is included. The analysis includes Net Energy Metered ("NEM") customers. The evaluation also develops *ex-ante* load impacts for both rates, with the evaluations conforming to the Load Impact Protocols adopted by the CPUC in D-08-04-050.

The TOU periods for both rates are centered around an on-peak period of 4 p.m. to 9 p.m. on non-holiday weekdays, which is surrounded by morning and evening off-peak periods, and an overnight super-off-peak period. The super-off-peak hours are longer for weekends and holidays as well as during the months of March and April.

The *ex-post* impact evaluations for both rates apply difference-in-differences analysis methods that involve selecting quasi-experimental matched control groups and then comparing the usage of treatment and control group customers on relevant days or time periods, where the comparisons are then adjusted by usage differences on pre-treatment or non-event days. The control groups were selected by matching each treatment customer to one of an initial sample of eligible non-treatment customers in relevant population segments (*e.g.*, climate zone, CARE status, and enrollment in SDG&E's Reduce Your Use, or RYU, program), based on the closest match of load profiles.

The count of customers that transitioned from EVTOU2 to EVTOU5 grew from 1,796 in October 2019 to 2,322 in September 2020. Peak load impacts are similar across all months, apart from October, which had the largest per-customer load reduction of 0.28 kWh/h during the peak period.

EVTOU2 customer enrollment increased over the study period from 7,220 to 7,799. Likewise, EVTOU5 customer enrollment increased from 7,330 to 11,186. Peak period load impacts of EVTOU2 and EVTOU5 customers were larger in the Inland climate zone. Both rates have more customers in the Coastal climate zone. The TOU peak load impacts were largest during the summer period for both rates. Specifically, the average EVTOU2 customer TOU peak load impact was 0.20 kWh/h in summer and 0.08 kWh/h in winter. The average EVTOU5 customer TOU peak load impact was 0.31 kWh/h in summer and 0.25 kWh/h in winter.

The aggregate energy consumed by customers in the VGI pilot decreased significantly as a result of the Covid-19 pandemic. The reduction was greatest for the workplace charging stations while there was only a slight decrease for at-home charging. A comparison of high and low-price day outcomes suggests that VGI pricing can be an effective means of reducing EV charging during system emergencies or when capacity margins are low.

Executive Summary

This report documents *ex-post* and *ex-ante* load impact evaluations for San Diego Gas and Electric Company's ("SDG&E") customers who are on the voluntary electric vehicle (EV) TOU rates, EVTOU2 and EVTOU5. Additionally, an analysis of SDG&E's vehicle grid integration (VGI) pilot is included. The analysis includes Net Energy Metered ("NEM") customers. The evaluation also develops *ex-ante* load impacts for both rates, with the evaluations conforming to the Load Impact Protocols adopted by the CPUC in D-08-04-050.

ES.1 Resources Covered

The TOU periods for both rates are centered around an on-peak period of 4 p.m. to 9 p.m. on non-holiday weekdays, which is surrounded by morning and evening off-peak periods, and an overnight super-off-peak period. The super-off-peak hours are longer for weekends and holidays as well as during the months of March and April.

ES.2 Evaluation Methodologies

The difficulty in evaluating EVTOU customers arises from not knowing when customers adopt an electric vehicle and begin charging at home. There are, however, customers that transitioned from rate EVTOU2 to EVTOU5. We can reasonably assume that customers that were on the EVTOU2 rate owned an electric vehicle during that time. This provides us the opportunity to evaluate the TOU load impact for customers that switch between rates EVTOU2 and EVTOU5.

The *ex-post* impact evaluations apply difference-in-differences analysis methods that involve selecting quasi-experimental matched control groups and then comparing the usage of treatment and control group customers on relevant days or time periods, where the comparisons are then adjusted by usage differences on pre-treatment or non-event days. The control groups were selected by matching each treatment customer to one of an initial sample of eligible non-treatment customers in relevant population segments (*e.g.*, climate zone, CARE status, solar PV size, and enrollment in SDG&E's Peak Time Rebate Reduce Your Use, or PTR-RYU, program), based on the closest match of load profiles.

As separate analysis is done for customers that transition from a standard tiered rate to one of the whole-house EVTOU rates. Evaluating the load impacts for these customers is plagued by not knowing when a customer adopts their electric vehicle. For many, it is likely highly correlated with enrolling in one of the EVTOU rates. However, there may be customers that had their electric vehicle for the entire analysis period, even prior to enrolling in an EVTOU rate. The key component for evaluating the TOU load impact of these customers is to identify which customers had their electric vehicle for the entire analysis period. To do this, we estimate customer-specific structural breaks in usage. Customers that do not exhibit a statistically significant change in usage are assumed to not have adopted an electric vehicle during the analysis period but, rather, beforehand. Such customers represent the set that we assume have an electric vehicle for the entire

analysis period. The *ex-post* load impacts are subsequently estimated using a before/after analysis and represent usage changes as a result of the TOU rate, and not from adopting an electric vehicle.

For the VGI Pilot evaluation, separate analyses are conducted for workplace and "home" charging (*i.e.*, the charging at multi-family dwellings), for two reasons: the charging behavior appears to differ at the two location types, especially by hour of day; and only workplace charging sessions allow us to compare behavior when the session is billed to the driver rather than the host.

ES.3 Ex-Post Load Impacts

ES.3.1 TOU peak load impacts – EVTOU2 to EVTOU5

Table ES.1 summarizes peak period loads and load impact estimates for customers who switched from EVTOU2 to EVTOU5 for the average summer (October 2019, and June through September 2020) and winter (November 2019 through May 2020) weekdays, by month. The count of customers that transitioned from EVTOU2 to EVTOU5 grew from 1,796 in October 2019 to 2,322 in September 2020.[1] Peak load impacts are similar across all months, apart from October, which had the largest per-customer load reduction of 0.28 kWh/h during the peak period.

Table ES.1: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Month*

Month	Climate Zone	Enrolled	Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	Ave. Temp.
Oct-19	All	1,796	2.55	0.51	1.42	0.28	71
Nov-19	All	1,860	2.62	0.24	1.41	0.13	60
Dec-19	All	1,905	3.23	0.26	1.70	0.14	56
Jan-20	All	1,979	2.83	0.21	1.43	0.11	55
Feb-20	All	2,406	3.11	0.22	1.29	0.09	57
Mar-20	All	2,066	2.48	0.24	1.20	0.12	57
Apr-20	All	2,097	2.56	0.19	1.22	0.09	63
May-20	All	2,143	2.56	0.14	1.19	0.07	70
Jun-20	All	2,172	2.79	0.24	1.28	0.11	72
Jul-20	All	2,218	3.45	0.36	1.55	0.16	74
Aug-20	All	2,279	4.64	0.23	2.04	0.10	78
Sep-20	All	2,322	4.69	0.23	2.02	0.10	78

[1] There were 397 incremental EVTOU2 to EVTOU5 customers with quality load data that were used in the regressions for estimating the EVTOU2 to EVTOU5 load impact.

Table ES.2 summarizes results by season and climate zone. Customers in the Coastal climate zone exhibit a larger TOU peak period response than the Inland climate zone during the summer period and a lower response during the winter period. The aggregate response is larger for the Coastal climate zone because there are more customers enrolled.

Table ES.2: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Season & Climate Zone*

Season	Climate Zone	Enrolled (Average)	Aggregate		Per-Customer		Ave. Temp.
			Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	
Summer	Coastal	1,509	2.43	0.25	1.61	0.17	73
	Inland	648	1.18	0.07	1.82	0.11	78
	All	**2,157**	**3.61**	**0.32**	**1.68**	**0.15**	**75**
Winter	Coastal	1,441	1.89	0.12	1.31	0.08	61
	Inland	624	0.88	0.08	1.41	0.13	58
	All	**2,065**	**2.77**	**0.20**	**1.34**	**0.10**	**60**

ES.3.2 TOU peak load impacts – Standard Tiered Rate to EVTOU2

Table ES.3 summarizes the EVTOU2 rate average reference loads and TOU load impacts for the TOU peak period (*i.e.*, 4 p.m. to 9 p.m.), for the average weekday *by month*, on an aggregate and per-customer basis. Enrollment slightly increased throughout the period, with the numbers of enrolled customers growing from 7,220 in October 2019 to 7,799 in September 2020.[2] Differences in percentage load impacts across seasons is driven by load impacts of NEM customers.

[2] The enrollment numbers in the tables differ from the number of customers used in the regression models, which is a subset of customers that have all the required data for conducting the *ex-post* load impact analysis. Specifically, there were 394 incremental customers on the EVTOU2 rate with quality load data that were used in estimating the TOU load impacts. The aggregate TOU load impacts are then scaled to total enrollments.

Table ES.3: TOU Peak Load Impacts for EVTOU2 Customers
– Average Weekday by Month

Month	Climate Zone	Enrolled	Aggregate		Per-Customer		Ave. Temp.
			Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	
Oct-19	All	7,220	10.29	1.21	1.43	0.17	71
Nov-19	All	7,244	10.49	0.49	1.45	0.07	60
Dec-19	All	7,280	12.27	0.55	1.68	0.08	56
Jan-20	All	7,403	10.97	0.50	1.48	0.07	56
Feb-20	All	7,462	10.02	0.48	1.34	0.06	57
Mar-20	All	7,528	9.40	0.96	1.25	0.13	57
Apr-20	All	7,562	9.20	1.01	1.22	0.13	63
May-20	All	7,605	8.59	0.53	1.13	0.07	69
Jun-20	All	7,655	9.70	1.38	1.27	0.18	72
Jul-20	All	7,702	11.12	1.49	1.44	0.19	74
Aug-20	All	7,719	15.44	1.67	2.00	0.22	78
Sep-20	All	7,799	15.02	1.60	1.93	0.21	78

Table ES.4 shows results by season and climate zone. The peak hour load impacts in the Inland climate zone are more than double than the Coastal climate zone. Even with less customers, the Inland aggregate load impacts are larger.

Table ES.4: TOU Peak Load Impacts for EVTOU2 Customers
– Average Weekday by Season & Climate Zone

Season	Climate Zone	Enrolled (Average)	Aggregate		Per-Customer		Ave. Temp.
			Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	
Summer	Coastal	5,337	8.45	0.72	1.58	0.13	73
	Inland	2,282	3.89	0.78	1.70	0.34	78
	All	**7,619**	**12.33**	**1.49**	**1.62**	**0.20**	**74**
Winter	Coastal	5,233	7.26	0.22	1.39	0.04	61
	Inland	2,208	2.85	0.41	1.29	0.18	58
	All	**7,441**	**10.11**	**0.63**	**1.36**	**0.08**	**60**

ES.3.3 TOU peak load impacts – Standard Tiered Rate to EVTOU5

Table ES.5 summarizes the EVTOU5 rate average reference loads and TOU load impacts for the TOU peak period (*i.e.*, 4 p.m. to 9 p.m.), for the average weekday *by month*, on

an aggregate and per-customer basis. Enrollment additions continued throughout the period, with the numbers of enrolled customers rising from 7,330 in October 2019 to 11,186 in September 2020.[3] The per-customer load impacts are positive across seasons. The largest per-customer load impact of 0.33 kWh/h occurs in August.

Table ES.5 TOU Peak Load Impacts for EVTOU5 Customers
– Average Weekday by Month

			Aggregate		Per-Customer		
Month	Climate Zone	Enrolled	Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	Ave. Temp.
Oct-19	All	7,330	9.69	1.94	1.32	0.26	71
Nov-19	All	7,695	11.13	2.09	1.45	0.27	60
Dec-19	All	8,121	13.56	2.35	1.67	0.29	56
Jan-20	All	8,763	12.89	2.42	1.47	0.28	56
Feb-20	All	9,173	12.24	2.46	1.33	0.27	57
Mar-20	All	9,559	10.94	1.98	1.14	0.21	57
Apr-20	All	9,838	11.30	2.11	1.15	0.21	63
May-20	All	10,040	11.95	2.81	1.19	0.28	70
Jun-20	All	10,280	12.33	2.83	1.20	0.28	72
Jul-20	All	10,568	14.53	3.08	1.37	0.29	74
Aug-20	All	10,867	21.02	3.56	1.93	0.33	78
Sep-20	All	11,186	21.08	3.50	1.88	0.31	78

Table ES.6 shows results by season and climate zone. The Coastal climate zone has nearly twice the number of enrolled customers. During the summer period, the average per-customer load impact and temperature was higher for the Inland climate zone at 0.43 kWh/h and 78 degrees Fahrenheit. The per-customer winter load impacts are similar between climate zones. Aggregate load impacts are greater in the Coastal climate zone during both seasons because of the differences in enrollment numbers.

[3] The enrollment numbers in the tables differ from the number of customers used in the regression models, which is a subset of customers that have all the required data for conducting the *ex-post* load impact analysis. Specifically, there were 2,560 incremental customers on the EVTOU5 rate with quality load data that were used in estimating the TOU load impacts. The aggregate TOU load impacts are then scaled to total enrollments.

Table ES.6: TOU Peak Load Impacts for EVTOU5 Customers
– Average Weekday by Season & Climate Zone

Season	Climate Zone	Enrolled (Average)	Aggregate		Per-Customer		Ave. Temp.
			Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	
Summer	Coastal	6,657	10.08	1.65	1.51	0.25	73
	Inland	3,389	5.77	1.46	1.70	0.43	78
	All	**10,046**	**15.86**	**3.11**	**1.58**	**0.31**	**75**
Winter	Coastal	5,999	8.36	1.64	1.39	0.27	61
	Inland	3,028	3.56	0.59	1.18	0.20	59
	All	**9,027**	**11.92**	**2.23**	**1.32**	**0.25**	**60**

ES.3.4 VGI Pilot Evaluation Study Findings

The Covid-19 pandemic had a large impact on the frequency of charging electric vehicles and, consequently, the energy demanded. The reduction was greatest for the workplace stations while there was only a slight decrease for at-home charging

A comparison of high and low-price outcomes provides a scenario that represents the value of the program during extreme circumstance. The timing of the load impacts suggests a higher reliability value for the application of VGI to home charging, as there are significant load impacts during the RA window (HE17 to 21). In contrast, the workplace RTD load impacts, while significant in magnitude, are concentrated much earlier in the day (peaking from HE11 to 14). These findings suggest that VGI pricing can be an effective means of reducing EV charging during system emergencies or when capacity margins are low.

A regression model at the session level reflect interesting and intuitively appealing results: EV customers who pay for the charging session are sensitive to the electricity price, while EV customers who do not pay for the charging session are not.

ES.4 Ex-Ante Load Impacts

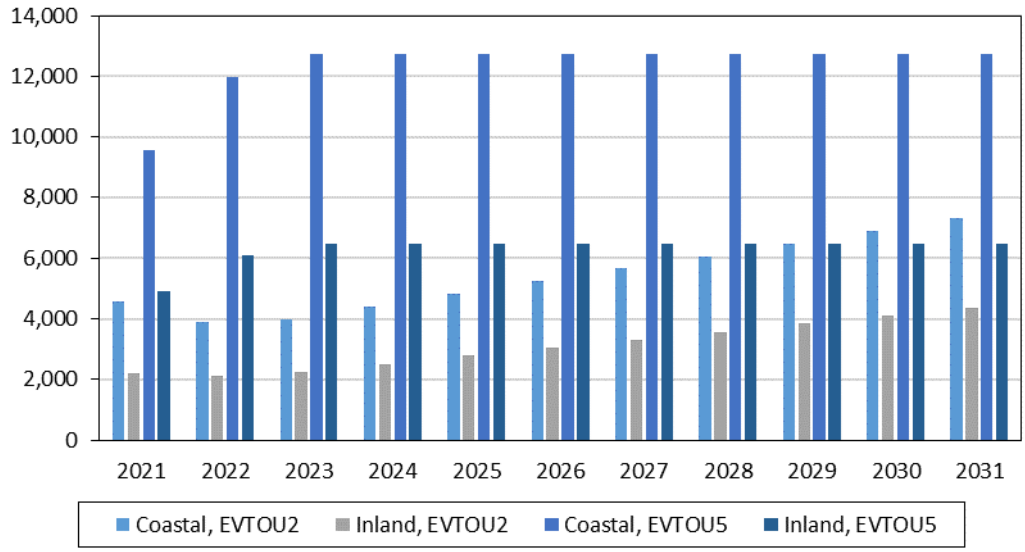
For the *ex-ante* analysis of each rate's TOU load impact, hourly percentage load impacts from the *ex-post* analysis (developed from seasonal values) are applied to weather-sensitive reference loads.

ES.4.1 Enrollment forecast

Figure ES.1 shows SDG&E's enrollment forecasts for the EVTOU2 and EVTOU5 rates. Enrollment is anticipated to decrease slightly until 2023 for EVTOU2 customers. Afterwards, EVTOU2 enrollment is forecasted to increase until nearly doubled by the

end of the forecast period. Enrollment in EVTOU5 is forecasted to increase 33 percent by 2033 and then remain steady thereafter. The aggregate EVTOU5 load impact is expected to be greater in the Coastal climate zone than in the Inland because of twice the number of enrolled customers.

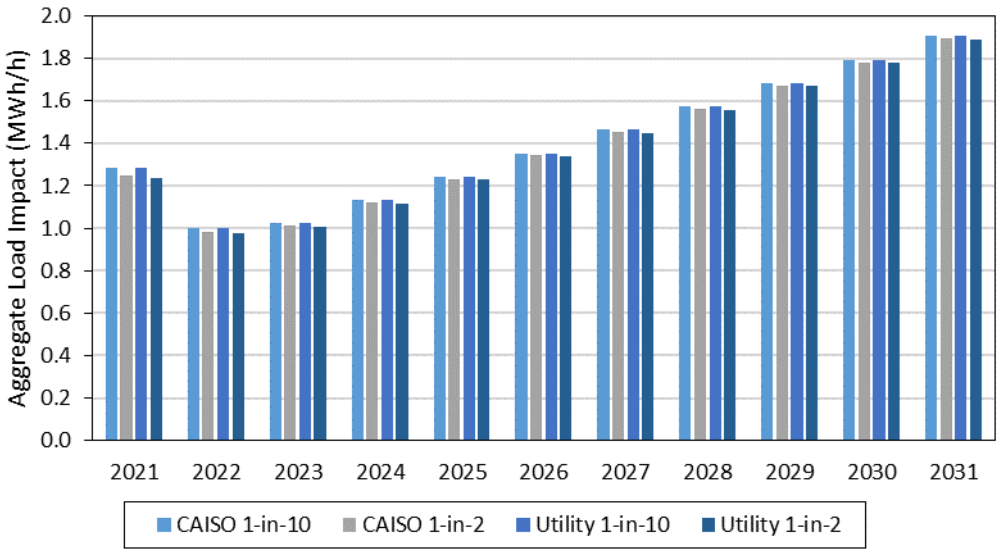
Figure ES.1: Enrollments in EVTOU Rates



ES.4.2 *Ex-Ante* load impacts –EVTOU2

Figure ES.2 shows the aggregate average August weekday TOU load impacts for EVTOU2 customers over the forecast period, differentiated by weather scenario. The load impacts are largest for the CAISO and Utility 1-in-10 scenarios, which have equivalent temperatures for the average August weekday. (TOU load impacts are largest for the Utility 1-in-10 scenarios on monthly peak days.) Enrollment changes over time drive the aggregate impacts lower in 2022 and higher thereafter.

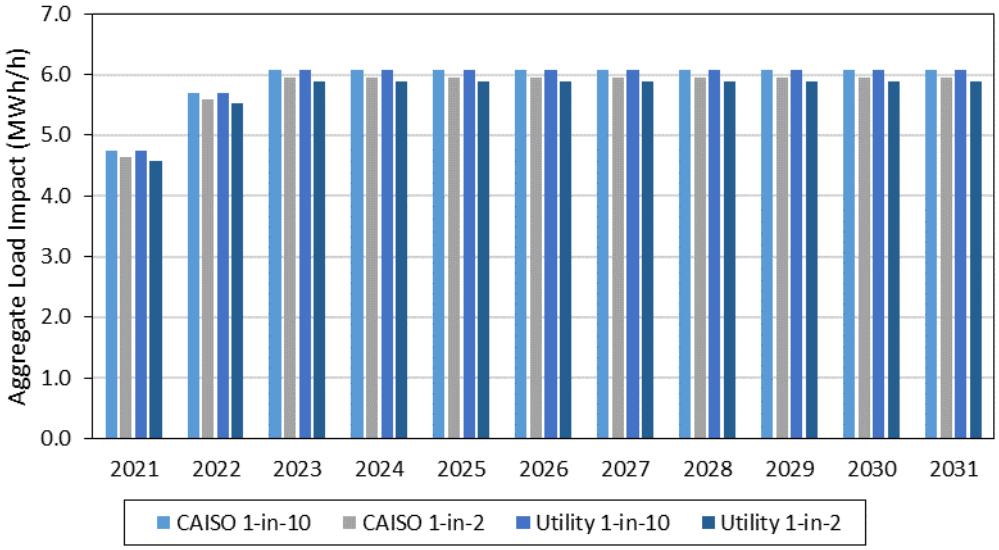
Figure ES.2: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)



ES.4.3 *Ex-Ante* load impacts –EVTOU5

Figure ES.3 shows the aggregate average August weekday TOU load impacts for EVTOU5 over the forecast period, differentiated by weather scenario. The load impacts are largest for the CAISO and Utility 1-in-10 scenarios, which have equivalent temperatures for the average August weekday. (TOU load impacts are largest for the Utility 1-in-10 scenarios on monthly peak days.) Enrollment in EVTOU5 is expected to increase until 2023 and then remain constant, resulting in the aggregate load impact changes between years.

Figure ES.3: Aggregate TOU Load Impacts (MWh/h) – *EVTOU5* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)



1. Introduction and Purpose of the Study

This report documents *ex-post* and *ex-ante* load impact evaluations for San Diego Gas and Electric Company's ("SDG&E") voluntary electric vehicle (EV) TOU rates, EVTOU2 and EVTOU5. Additionally, an analysis of SDG&E's vehicle grid integration (VGI) pilot is included.

The evaluation also develops *ex-ante* load impacts for both rates, with the evaluations conforming to the Load Impact Protocols adopted by the CPUC in D-08-04-050.

The TOU periods in the two rates are centered around an on-peak period of 4 to 9 p.m. on non-holiday weekdays, which is surrounded by morning and evening off-peak periods, and an overnight super-off-peak period. The super-off-peak hours are longer for weekends and holidays as well as during the months of March and April. The EVTOU rates differ in their prices per TOU period. Customers on the EVTOU5 rate incur a $16 basic service fee that is not shared by customers on the EVTOU2 rate.

This report also provides an evaluation of SDG&E's VGI pilot program. VGI Program Facilities are electric vehicle charging stations that are installed, owned and operated by SDG&E, pursuant to D.16-01-045. VGI Program Facilities are located at workplaces and multi-unit dwellings. The VGI rate for charging at one of these facilities is dynamic and consists of an hourly base rate, an hourly commodity base rate, and an hourly distribution base rate. In this evaluation, we will attempt to assess the following: (1) whether the duration of a charging session is affected by the hourly prices; and (2) whether the total energy of a charging session is affected by the hourly prices.

The report is organized as follows. Section 2 contains descriptions of the EVTOU2 and EVTOU5 rates; Section 3 describes the evaluation methods used in the study; Section 4 contains the TOU *ex-post* load impact results for EVTOU2 and EVTOU5 customers; Section 5 describes the VGI pilot evaluation findings; Section 6 describes the methods used to develop the *ex-ante* load impacts; Section 7 contains the *ex-ante* load impact results; Section 8 provides a series of comparisons of *ex-post* and *ex-ante* results; and Section 9 provides recommendations.

2. Description of Rates

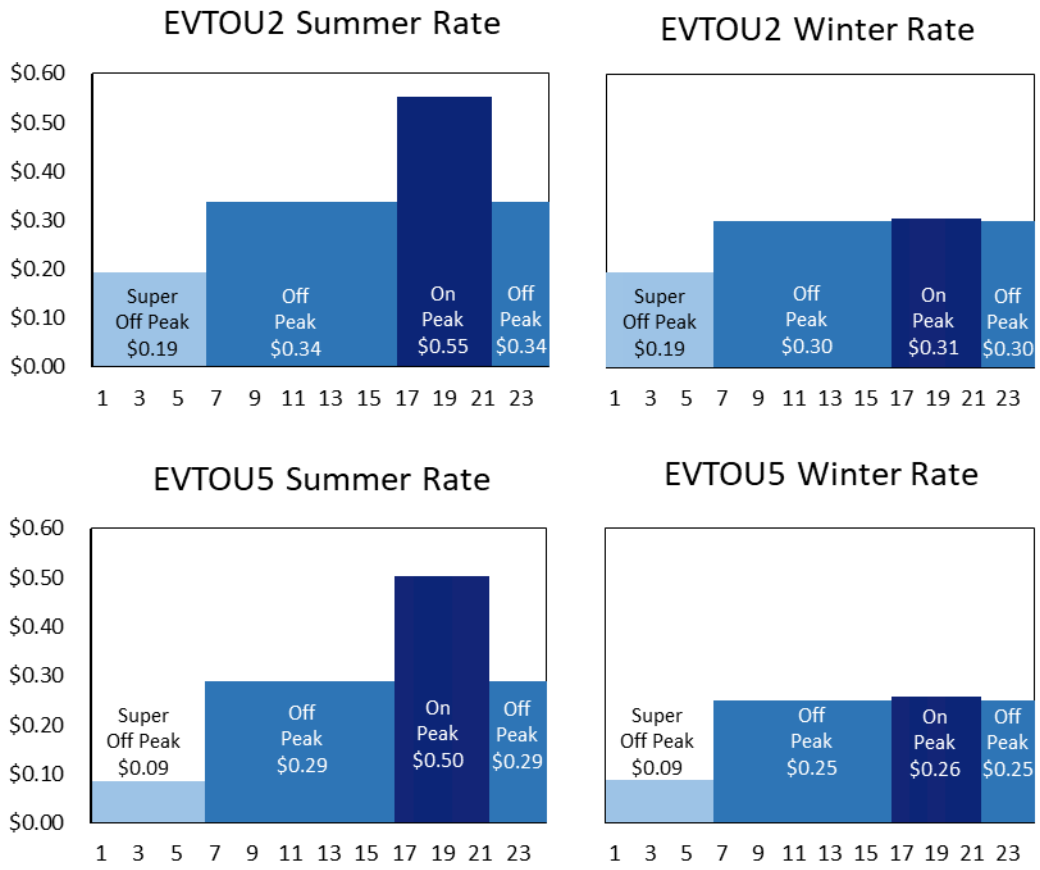
As noted in the introduction, both EVTOU rates have an on-peak period of 4 to 9 p.m. on non-holiday weekdays, with morning and evening off-peak periods before and after, and an overnight super-off-peak period. The super-off-peak hours are longer for weekends and holidays as well as during the months of March and April.

Figure 2.1 depicts the total rates by TOU period and season for each EVTOU rate.[4] The EVTOU5 rate $0.11 less than the EVTOU2 rate during the super off-peak period and

[4] The 2020 EVTOU2 rate can be found at http://regarchive.sdge.com/tm2/pdf/ELEC_ELEC-SCHEDS_EV-TOU-2_2020.pdf.
The 2020 EVTOU5 rate can be found at http://regarchive.sdge.com/tm2/pdf/ELEC_ELEC-SCHEDS_EV-TOU-5_2020.pdf.

$0.05 less during all other periods. Furthermore, the EVTOU5 rate includes a basic service fee of $16 whereas the EVTOU2 includes a minimum daily bill of $0.338.

Figure 2.1: EV Rate Time-of-Use Periods and Prices



The VGI pilot program includes a number of VGI Program Facilities which provide electric vehicle charging under the VGI rate.[5] The dynamic rate consists of three components: an hourly base rate, an hourly commodity base rate, and an hourly distribution base rate. The commodity base rate includes an adjustment based on the California Independent System Operator (CAISO) day-ahead hourly price, an adder to reflect the system's top 150 system peak hours, and an adjustment to reflect day-of CAISO surplus energy hours. The hourly distribution base rate includes an adder to reflect the top 200 annual hours of peak demand for the individual circuit feeding the VGI charging station. The rates are applicable to either the individual vehicle customer charging through the VGI Program Facility or the Site Host providing the charging.[6]

[5] VGI Program Facilities are installed, operated, and maintained by SDG&E, pursuant to D.16-01-045, and are located at workplaces and multi-unit dwellings.

[6] The Site Host is an applicable site that allows SDG&E to install, operate, and maintain VGI Program Facilities on its property. Site Hosts agree to participate in and follow the requirements of the VGI

3. *Ex-Post* Evaluation Methodology

The primary objectives of the *ex-post* impact evaluation were described in Section 1. This section describes the data and specific methods that were used in the study.

3.1 Data

An analysis that addresses each of the load impact objectives listed in Section 1 requires the following types of data:

- *Customer* information for the residential EV customers and potential control group customers (*e.g.*, location indicator for matching to climate zone, CARE status, NEM status and characteristics);
- Billing-based *interval load data* (*i.e.*, hourly loads for each enrollee, and potential control group customers), for October 2018 through September 2020;
- *Weather data* (*i.e.*, hourly temperatures and other variables for the relevant time period, for both climate zones—coastal and inland);

3.2 Analysis Methods

The evaluation approach used in this study includes implementing a difference-in-differences regression analysis using data for EVTOU participants and matched control group customers. The analysis involves three steps. First, CA Energy Consulting requests hourly load data for the enrollees and potential control group customers for the current year and the previous year (pre-enrollment year for new enrollees). Second, matched control group customers are selected for the EV enrollees, as described below. Third, fixed-effects panel regression models are estimated, which produce difference-in-differences estimates of average TOU period load impacts for both EVTOU2 and EVTOU5 rates. Evaluation of EVTOU customers and the VGI pilot requires additional assumptions and methods as well. Therefore, this section details the core methods used in the analysis while Section 3.3 and 3.4 provide additional methods for EVTOU customers and the VGI pilot, respectively.

3.2.1 Evaluation design and control group matching

The difference-in-differences evaluation is a quasi-experimental approach that compares the usage of treatment and matched control group customers on relevant days or time periods, adjusted by their usage differences on pre-treatment days. The control groups were selected by matching each treatment customer to one of a sample of eligible non-treatment customers in relevant population segments (*e.g.*, climate zone, CARE status, and enrollment in PTR-RYU), based on the closest match of load profiles. The initial samples of eligible control group customers were developed as seven-to-one samples by segment from the eligible population of SDG&E residential customers.

program. The Site Host determines if the VGI Program Facilities on its property will be billed to the driver or the Site Host.

For analyzing TOU impacts, for both EVTOU2 and EVTOU5 customers, only incremental treatment customers were used in the analysis and matched based on loads in the pre-treatment period (*i.e.,* October 2018 through September 2019). Only incremental customers are used in the TOU load impact study because these customers have enough pre-treatment data to provide a quality difference-in-difference analysis. The matching and regression analyses are separated by season, thus allowing different threshold dates that define incremental customers.[7] Specifically, incremental customers for the winter analysis are those that enrolled after June 1, 2019 while incremental customers for the summer analysis are those that enrolled after October 1, 2019. The incremental TOU customers were matched based on two pairs of hourly loads for each season – one for all weekdays, and one for a subset of the hottest (or coldest) weekdays. Matching for the *winter* season used data for November 2018 through May 2019, while the *summer* season used data for October 2018 and June through September of 2019.

Matching was based on Euclidean distance minimization between treatment and potential control group customer loads. This approach minimizes the difference between a standardized usage metric of the treatment and potential control group customers as shown in the equation below.

$$Distance_{T,C} = \sqrt{(T_1 - C_1)^2 + (T_2 - C_2)^2 \ldots + (T_n - C_n)^2}$$

In this equation, the *T* variables represent treatment customer characteristics and the *C* variables represent the corresponding eligible control group customer characteristics. For the EVTOU analysis, the customer characteristics include the average hourly usage on weekdays and hot/cold days for the summer/winter match (48 variables).[8] Treatment and potential control customers are also segmented by climate zone and CARE status. Each enrolled customer is compared to each potential control group customer within their segment, using the distance measure. When the minimum distance statistic is found, the potential control group customer associated with that value is selected as the match for that EVTOU customer. Potential control group customers were allowed to be matched with replacement (*i.e.*, matched to multiple enrolled customers).

NEM customers are matched similarly, with three major distinctions. First, only customers that are NEM for the entire analysis period and have not made changes to their solar PV system are included.[9] Second, NEM treatment customers must be

[7] The seasons defined for matching are summer (June through October) and winter (November through May).

[8] Hot/cold days are among the highest/lowest 20th percentile in terms of CDD or HDD temperature values. Hot/cold days are selected separately by climate zone.

[9] With a matched control group, it is essential to create a counterfactual that mimics any changes a treatment customer faces. It becomes increasingly unlikely to find a suitable match for customers that become NEM during the analysis period or change their solar PV characteristics because the best practice would be to search for a control customer that made comparable changes at parallel points in time. Additionally, including controls in a regression for these changes is limited by the amount of overlap

matched to NEM control customers that have comparable solar photovoltaic generation capacity sizes.[10] Third, customers with large changes in net profiles between periods are not used in the analysis because the differences are more likely caused by unobserved structural changes to a customer's solar PV system. The methodology and thresholds used for identifying NEM customers with large changes in usage and subsequently removed from the analysis is explained in more detail in Appendix C. Each of these requirements helps prevent estimating load impacts that are confounded by differences in solar generation capacity between periods and/or between the treatment and control groups, as opposed to only a behavioral response to TOU rates.[11]

3.2.2 Fixed-effects panel regression models

The formal *ex-post* load impact estimates are based on *fixed-effects* panel regression models. These models are appropriate in situations like the current study, in which observed data are available for both multiple individual customers (cross-section) and multiple days, or time periods (time-series). The advantages of estimating such models include: 1) accounting for the effect of relevant factors on the variation in usage across customers and days, 2) accounting for the effects of weather conditions on usage, and 3) the availability of standard errors around the estimated load impact coefficients, thus allowing construction of *confidence intervals*.

The fixed-effects regression was used to estimate average weekday EVTOU load impacts (estimated separately for the EVTOU2 and EVTOU5 customers). In addition to estimating each load impact type separately by rate, the load impacts were estimated separately for NEM customers within each rate.

Each model addresses the objective of estimating hourly *ex-post* load impacts at the program level by estimating a set of twenty-four separate fixed-effects models, one for each hour of the day. These models allow customer-specific constant terms, but estimate the same coefficient, effectively representing an average load impact across the included treatment customers, for variables that do not vary across customers (*e.g.*, the occurrence of an event day).

3.2.3 *Ex-post* models for estimating TOU load impacts

To obtain TOU load impacts for EV customers, a distinct model is estimated for each required result. For example, to obtain the average TOU load impacts on August non-

between the change and becoming a EVTOU customer. Essentially, it is more difficult to statistically disentangle effects the closer they occur to each other.

[10] NEM customers are segmented only by solar PV size, rounded to the next integer level (capacity sizes greater than 12 kW are a separate segment).

[11] For example, a high premise usage treatment customer with a larger solar generation system may be matched to a lower premise usage control customer with a smaller solar generation system based on similar net load profiles. If conditions are met so that solar generation is larger in the post-period, then any analysis based on net load profiles will exhibit that the treatment customer reduced their usage, relative to their own pre-treatment usage as well as relative to the control customer's usage.

holiday weekdays, a model is estimated that includes only days of that day type.[12] In this case, the model is simplified to include customer and date fixed effects, plus a variable to estimate the load impact (*i.e.*, the coefficient β_1). Separate models are estimated by rate (*e.g.,* EVTOU2 and EVTOU5), hour, month, day-type (*i.e.*, average weekday versus peak month day), applicable customer groups (*e.g.*, climate zone, NEM), where the customer-level fixed-effects models are of the following form:[13]

$$kWh_{c,d} = \beta_0 + \beta_1 \times (EVTOU_c \times Post_{c,d}) + \Sigma_{Cust} (\beta_{2,Cust} \times C_c) + \Sigma_{date} (\beta_{3,date} \times D_{date}) + \beta_4 \times TOU_{c,d} + \beta_5 \times AC_Evt_{c,d} + \varepsilon_{c,d}$$

The variables and coefficients in the equation are described in Table 3.1. Incremental customers are used to estimate the EVTOU load impacts in each regression. Results are then scaled to the program level of enrollments.

[12] In cases where insufficient numbers of observations were available, the approach was modified by combining day-types into seasons that correspond to TOU periods (*i.e.,* summer is June through October, winter is November through February and May, and a separate winter season for March and April). Specifically, observations were combined for all season-specific weekdays to estimate a constant season percentage load impact (*i.e.,* $PctLI_{Season} = LI_{Season}/(Obs_{Season} + LI_{Season})$). The season-specific percentage load impacts are then used to calculate monthly average weekday or system peak day reference loads (*i.e.,* $Ref_{Daytype}=Obs_{Daytype}/(1-PctLI_{Season})$ and level load impacts (*i.e.,* $LI_{Daytype} = Ref_{Daytype}*PctLI_{Season}$).

[13] Note that the customer and date fixed effects remove the need for us to include stand-alone TOU_c and $Post_{c,d}$ variables. The former is perfectly collinear with the customer's fixed effect and the latter is perfectly collinear with a combination of date fixed effects.

Table 3.1: Description of Variables Used in the EVTOU Analysis Regressions

Symbol	Description
$kWh_{c,d}$	Load in a particular hour for customer *c* on date *d*
$EVTOU_c$	Variable indicating whether customer *c* is an EVTOU (1) or Control (0) customer
$Post_{c,d}$	Variable indicating that date *d* is in the post-enrollment period for customer *c*
$TOU_{c,d}$	Variable indicating whether customer *c* is on a, non-EVTOU, TOU rate on date *d*[14]
$AC_Evt_{c,d}$	Variable indicating that date *d* is an *AC Saver Day Of* event day (1=event, 0 if not) for customer *c*
β_0	Estimated constant coefficient
β_1	Estimate of the EVTOU load impact
$\beta_{2,Cust}$ and $\beta_{3,date}$	Estimated customer and date fixed effects
β_4	Estimate of average TOU load impact (non EVTOU)
β_5	Estimated average *AC Saver Day Of* event-day load impacts
C_c	Variable indicating that the observation is associated with customer *c*
D_{date}	Variable indicating that the observation is for date *d*
$\varepsilon_{c,d}$	Error term

3.2.4 Calculating uncertainty-adjusted load impacts

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. In the case of *ex-post* load impacts, the coefficients that represent the estimated load impacts in the fixed-effects regressions are not estimated with certainty, but with a range of uncertainty indicated by the variance of the estimates. Therefore, the uncertainty-adjusted load impacts are based on the variances associated with the estimated load impact coefficients (*e.g.*, the event-day or treatment-period coefficients in the twenty-four hourly regressions).

The uncertainty-adjusted scenarios are then simulated under the assumption that each hour's load impact is normally distributed with the mean equal to the sum of the estimated load impacts and the standard deviation equal to the square root of the sum of the variances of the errors around the estimates of the load impacts. Results for the 10th, 30th, 70th, and 90th percentile scenarios are generated from these distributions.

To develop the uncertainty-adjusted load impacts by TOU pricing period (*i.e.*, the bottom rows in the tables produced by the *ex-post* table generator), additional sets of regression models are estimated in which the load impact variable is constrained to be the same across the applicable hours. The associated standard errors are used to develop the uncertainty-adjusted load impacts in the same manner described above.

[14] For customers that switched between a standard rate and TOU rate before transitioning to an EVTOU rate.

3.2.5 Validity assessment

Because a control-group approach is being employed, the validity assessment focuses on comparisons of treatment and control-group loads for pre-treatment loads. Statistics such as the mean absolute percentage error (MAPE) and mean percent error (MPE), which provide formal estimates of the percent differences between treatment and control group loads, are also reported. The MAPE offers a measure of accuracy while MPE offers a measure of bias.

3.3 Further Methods for EVTOU Analyses

Estimating TOU load impacts for customers that join one of the EVTOU rates provides additional challenges because there is no information regarding the type of electric vehicle a customer owns and, most importantly, the date when they begin charging their electric vehicle at home.[15] The basic evaluation of TOU load impacts is accomplished by determining how a customer changes their load behavior after joining the rate while accounting for changes in weather, day of the week, etc. However, if a customer joins an EVTOU rate at the same time as purchasing and charging an electric vehicle at home, then load impacts will reflect a change in response to both the EVTOU rate *and* to purchasing an electric vehicle.[16] Since we want to estimate the response to the EVTOU rate, our goal is to remove any response that occurs because of adopting an electric vehicle. This section provides analyses and methods that were implemented for EVTOU customers in the face of these challenges.

3.3.1 Transition from EVTOU2 to EVTOU5 Analysis

As mentioned, the difficulty in evaluating EVTOU customers arises from not knowing when customers adopt an electric vehicle and begin charging at home. There are, however, customers that transitioned from rate EVTOU2 to EVTOU5. We can reasonably assume that customers that were on the EVTOU2 rate owned an electric vehicle during that time. This provides us the opportunity to evaluate the TOU load impact for customers that switch between rates EVTOU2 and EVTOU5.

We evaluate customers that transitioned from EVTOU2 to EVTOU5 after October 1, 2019. This allows the use of October 1, 2018 through September 30, 2019 as a pre-treatment period (such as the TOU analyses described above). This analysis requires an additional restriction that, for customers that transitioned from EVTOU2 to EVTOU5, they must be enrolled on EVTOU2 for the entire period prior to the transition. If our

[15] SDG&E does not collect this information.

[16] Electric vehicle adoption does not have to coincide with switching to an EVTOU rate to affect the analysis. Any change in usage that isn't accounted for can bias a pre- vs post-analysis. Control groups help to account for changes that affect all customers, such as economic conditions. However, adopting an electric vehicle typically results in a substantial change in usage for the single customer. The EV adoption will therefore affect the results of a pre- vs post-analysis if it occurs at any point during the analysis period and is uncontrolled for. Furthermore, even if the date of EV adoption was known with certainty, there are statistical complications in separating out the EV adoption effect with the TOU effect depending on when these changes occur and how close they are to each other.

assumption that a customer enrolled on an EVTOU rate serves as a proxy for owning an electric vehicle is correct, then the additional restriction guarantees that the customer had an electric vehicle for the entire period and thus eliminates any usage response that occurs because of the adoption of an electric vehicle.[17]

Transitioning customers must be on EVTOU2 for the entire pre-treatment period. We also leverage customers that remained on EVTOU2 for the entire analysis period (October 1, 2018 through September 30, 2020) as a potential control group. Consequently, the evaluation for customers that transition from EVTOU2 to EVTOU5 is accomplished using the same difference-in-difference evaluation approach that is described above for the TOU analyses. That is, transitioned customers are matched to EVTOU2 customers using the Euclidean distance minimization approach. The load impact is subsequently estimated using a fixed effects regression model by different groups (*e.g.,* NEM, climate zone, season). Resulting load impact estimates reflect the incremental effect of switching rates from the EVTOU2 to EVTOU5.

3.3.2 Incremental EVTOU2 and EVTOU5 Analysis

Incremental EVTOU2 and EVTOU5 customers are defined as those that switch from a standard tiered rate to either the EVTOU2 or EVTOU5 rate after October 1, 2019. Evaluating the load impacts for these customers is plagued by not knowing when a customer adopts their electric vehicle. For many, it is likely highly correlated with enrolling in one of the EVTOU rates. However, there may be customers that had their electric vehicle for the entire analysis period, even prior to enrolling in an EVTOU rate.

The key component for evaluating the TOU load impact of these customers is to identify which customers had their electric vehicle for the entire analysis period. To do this, we analyze each customer's weekly usage to estimate an unknown structural break date with customer-specific regressions. The model essentially identifies the most likely date where there is a change to a customers' usage that isn't accounted for in the regression specification. The structural break is a statistical test which provides a level of statistical significance from which we can subsequently identify which customers *do not* have a statistically significant structural break in their usage level. Customers that do not exhibit a statistically significant change in usage are assumed to not have adopted an electric vehicle during the analysis period but, rather, beforehand. Such customers represent the set that we assume have an electric vehicle for the entire analysis period.

The following regression specification is estimated for each customer separately to account for changes in their average daily consumption each week:

$$kWh_w = \beta_0 + \beta_1 \times CDD60_w + \beta_2 \times HDD60_w + \Sigma_m (\beta_{3,m} \times Month_{w,m}) + \varepsilon_w$$

[17] A limitation of this analysis remains from unobservable information; that is, we do not know if a customer changes the type of electric vehicle they own during the analysis period. For example, the load needed to charge a Nissan Leaf will be different than an Audi e-tron SUV. These occurrences are likely uncommon and will not affect the analysis much with large samples.

The variables and coefficients in the equation are described in the Table 3.2.

Table 3.2: Description of Variables Used in the Identification of Electric Vehicle Adoption Regressions

Symbol	Description
kWh_w	Average daily kWh during week *w* (weekends, holidays, and event days excluded)
$CDD60_w$	Average cooling degree days[18] during week *w*
$HDD60_w$	Average heating degree days[19] during week *w*
$Month_w$	Monthly indicator variables
β_0	Estimated constant coefficient
β_1	Estimated effect of *CDD60* on daily kWh
β_2	Estimated effect of *HDD60* on daily kWh
$\beta_{3,m}$	Estimated effect of month *m* on daily kWh
ε_w	Error term

After each individual regression is estimated, a structural break test is performed using the residual values (*i.e.,* the difference between the predicted and observed values of average daily usage by week, which represent usage the model doesn't account for). The structural break test involves performing a Wald test for each possible break date in the sample.[20] The maximum value of the Wald test statistic over all days indicates the date of a structural break (that is unknown). A customer that has a supremum Wald statistic that *is not statistically significant* therefore provides no statistical evidence that a significant change in usage occurred at any point during the period.

We assume that incremental EVTOU customers that have no statistically significant structural break identified had (and charged) their electric vehicle for the entire period, even prior to adopting one of the EVTOU rates. This set of customers is used to estimate the incremental EVTOU2 and EVTOU5 load impacts by means of the regression specifications described above in Section 3.2.3. Separate TOU regressions are estimated by EVTOU rate, NEM, climate zone, and season.[21] Because we assume that these customers had an electric vehicle during the pre-treatment period, however, we do not match their loads to other potential control customers. Nonetheless, a control group of customers that have remained on EVTOU2 for the entire analysis period are included.

[18] Cooling degree days (CDD) are defined as MAX[0, (Max Temp + Min Temp) / 2 – 60], where Max Temp is the daily maximum temperature in degrees Fahrenheit and Min Temp is the daily minimum temperature. Customer-specific CDD values are calculated using data from the most appropriate weather station.

[19] Heating degree days (HDD) are defined as MAX[0, 60 – (Max Temp + Min Temp) / 2], where Max Temp is the daily maximum temperature in degrees Fahrenheit and Min Temp is the daily minimum temperature. Customer-specific HDD values are calculated using data from the most appropriate weather station.

[20] The Wald test provides a measure to assess whether a set of variables within or between a regression are statistically different from each other. In this case, Wald tests are calculated for differences in estimated coefficients from regressions estimated before and after potential break dates.

[21] As is done in the TOU analysis, only NEM customers that do not change their solar PV characteristics during the analysis period are included.

The control group provides a reference point for how customer usage changes in response to the COVID-19 pandemic in 2020.[22]

While this methodology proposes a creative solution to estimate TOU load impacts for incremental EVTOU customers, results should be viewed with full acknowledgement of its limitations. First, the methodology attempts to identify an *unknown* date for which a customer begins charging an electric vehicle at home. Because this date remains ultimately unknown, we cannot provide a summary of how accurately the model identifies electric vehicle adoption dates. Second, while changes in usage for electric vehicle adoption can be substantial, there may be cases where charging an electric vehicle doesn't significantly affect usage. If that occurs, the model may not identify a structural break, resulting in the customer being included in the analysis. Consequently, EVTOU load impacts may be overstated by including a new EV adopter (and including any associated increase in usage in the TOU load impact estimate). Third, and similarly, the structural break model will have difficulty in identifying a statistically significant structural break for customers that have a high variance in their usage from week to week. Such customers may then pass the test of no structural break (categorized as having EV for the entire period) and be included in the model when they adopted an EV during the analysis period. The implication would be an overstated EVTOU load impact. Fourth, and lastly, we may be removing customers that indicate a structural break when the change in usage is not because of EV adoption but instead as a response to the EVTOU rate. This would result in a conservative EVTOU load impact; however, we believe this is less likely to occur than the other caveats.

Appendix C provides results from the structural break tests.

3.4 VGI Pilot Evaluation Methods

For the VGI Pilot evaluation, separate analyses are conducted for workplace and "home" charging (*i.e.*, the charging at multi-family dwellings), for two reasons: the charging behavior appears to differ at the two location types, especially by hour of day; and only workplace charging sessions allow us to compare behavior when the session is billed to the driver rather than the host.

The model uses session-level data (*i.e.*, each data point is an instance of a driver plugging into a charging station). The workplace charging model is specified as follows:

$$kWh_s = \beta_0 + \beta_1 \times Price_s + \beta_2 \times (Price_s \times RTD_s) + \beta_3 \times Weather_s + \Sigma_h (\beta_{4,h} \times Start_hour_{s,h}) + \beta_5 \times COVID_d + Site + Driver + \varepsilon_s$$

The variables and coefficients in the equation are described in the Table 3.3.

[22] The EVTOU2 customers used as a control group for the incremental EVTOU analyses is the same set used as controls for the EVTOU2 to EVTOU5 analysis.

Table 3.3 Description of Variables Used in the VGI Evaluation Regressions

Symbol	Description
kWh_s	Total kWh during charging session *s*
$Price_s$	Average price during charging session *s*
RTD_s	Variable indicating that session *s* is billed to the driver (rather than the station host)
$Weather_s$	Weather variable reflecting average temperature during charging session *s*
$Start_hour_s$	Hour of day in which session *s* begins
$COVID_d$	an indicator variable for if day *d* is during the COVID-19 pandemic (*i.e,* post March 2020)
β_0	Estimated constant coefficient
β_1	Estimated effect of price in session kWh charged
β_2	Incremental estimated effect of price in session kWh charged for sessions billed to the driver
β_3	Estimated effect of weather on the charge quantity
$\beta_{4,h}$	Estimated effect of start hour *h* on the charge quantity
β_5	Estimated effect of Covid-19 pandemic on the charge quantity
Site	Charging site fixed effects
Driver	Driver fixed effects
ε_s	Error term

The two coefficients of primary interest are β_1 and β_2. The former represents the effect of price on the session's charging quantity while the latter represents the incremental price effect when the driver pays the bill. Our prior is that β_2 will be negative and statistically significant, reflecting greater price response when the driver pays the hourly prices.

A separate set of models of the effect of the session's charging price on the duration of the charging session take the same form as above, simply replacing the dependent variable with the duration of the charging session in hours.

The non-workplace models take the same form, but omit the interaction between RTD and price, as only RTD charging sessions exist at the multi-family dwelling charging stations.

The models described above use a charging session as the unit of observation and attempt to explain variations in the duration and quantity associated with each session. In addition to these statistical models, we provide descriptive figures focusing on the total hourly charging load across all stations of each type: workplace RTD, workplace RTH, and home RTD. These figures illustrate the effect of high VGI prices on total charging load.

4. EVTOU *Ex-Post* Load Impact Study Findings

This section presents the match quality and estimates of monthly peak TOU load impacts for the EVTOU analyses: EVTOU2 to EVTOU5, incremental EVTOU2, and incremental EVTOU5.

4.1 TOU control group matching results for EVTOU2 to EVTOU5 customers

Figures 4.1 and 4.2 illustrate the quality of the matches for customers who switched from EVTOU2 to EVTOU5. The figures show the average EVTOU2 load profile for treatment (transition to EVTOU5) and matched control-group (remain on EVTOU2) customer load profiles for the summer and winter months, respectively. Two pairs of loads are shown, one for all weekdays, and one for the hottest (or coldest) days. In the summer months, the mean percentage error (MPE) of the TOU profile compared to the control-group profile is 4.8 percent, while the mean absolute percentage error (MAPE) is 5.1 percent. In the winter months, the MPE is 4.5 percent and the MAPE is 4.6 percent.

Figure 4.1: EVTOU2 to EVTOU5 and Matched Control Group Load Profiles – *Summer*

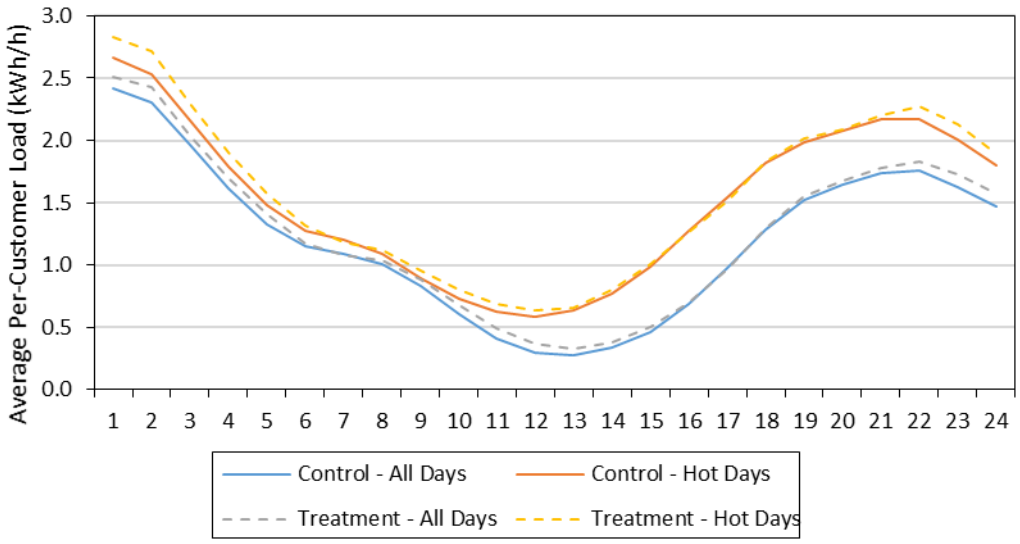
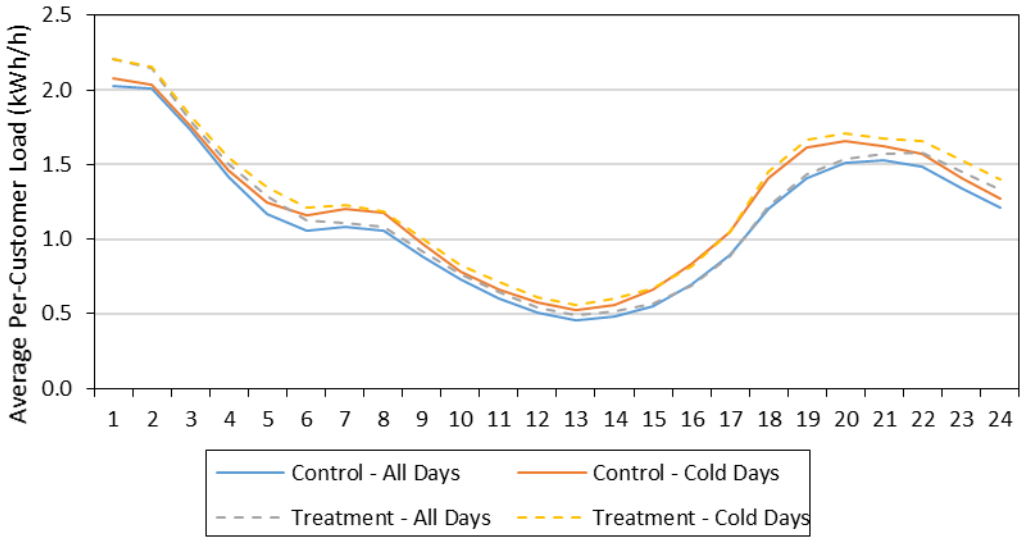


Figure 4.2: EVTOU2 to EVTOU5 and Matched Control Group Load Profiles – *Winter*



4.2 Ex-post TOU load impacts for EVTOU2 to EVTOU5 customers

This sub-section shows *ex-post* TOU load impact estimates for customers who switched from EVTOU2 to EVTOU5. Table 4.1 summarizes peak-period loads and load impacts for the average summer (October 2019, and June through September 2020) and winter (November 2019 through May 2020) weekdays, by month. The count of customers that transitioned from EVTOU2 to EVTOU5 grew from 1,796 in October 2019 to 2,322 in September 2020.[23] Peak load impacts are similar across all months, apart from October, which had the largest per-customer load reduction of 0.28 kWh/h during the peak period.

[23] There were 397 incremental EVTOU2 to EVTOU5 customers with quality load data that were used in the regressions for estimating the EVTOU2 to EVTOU5 load impact.

Table 4.1: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers
– Average Weekday by Month

Month	Climate Zone	Enrolled	Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	Ave. Temp.
Oct-19	All	1,796	2.55	0.51	1.42	0.28	71
Nov-19	All	1,860	2.62	0.24	1.41	0.13	60
Dec-19	All	1,905	3.23	0.26	1.70	0.14	56
Jan-20	All	1,979	2.83	0.21	1.43	0.11	55
Feb-20	All	2,406	3.11	0.22	1.29	0.09	57
Mar-20	All	2,066	2.48	0.24	1.20	0.12	57
Apr-20	All	2,097	2.56	0.19	1.22	0.09	63
May-20	All	2,143	2.56	0.14	1.19	0.07	70
Jun-20	All	2,172	2.79	0.24	1.28	0.11	72
Jul-20	All	2,218	3.45	0.36	1.55	0.16	74
Aug-20	All	2,279	4.64	0.23	2.04	0.10	78
Sep-20	All	2,322	4.69	0.23	2.02	0.10	78

Table 4.2 summarizes results by season and climate zone. Customers in the Coastal climate zone exhibit a larger TOU peak period response than the Inland climate zone during the summer period and a lower response during the winter period. The aggregate response is larger for the Coastal climate zone because there are more customers enrolled.

Table 4.2: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers
– Average Weekday by Season & Climate Zone

Season	Climate Zone	Enrolled (Average)	Aggregate		Per-Customer		Ave. Temp.
			Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	
Summer	Coastal	1,509	2.43	0.25	1.61	0.17	73
	Inland	648	1.18	0.07	1.82	0.11	78
	All	**2,157**	**3.61**	**0.32**	**1.68**	**0.15**	**75**
Winter	Coastal	1,441	1.89	0.12	1.31	0.08	61
	Inland	624	0.88	0.08	1.41	0.13	58
	All	**2,065**	**2.77**	**0.20**	**1.34**	**0.10**	**60**

Table 4.3 shows the effect of TOU on average daily usage by month. Customers that transitioned to EVTOU5 exhibited *increased* overall usage during nine of the twelve months compared with their usage under EVTOU2, particularly during non-peak hours.

The overall effect is an average annual *increase* of about 1.16 kWh/h per customer per day.

Table 4.3: TOU Average *Daily* Load Impacts for EVTOU2 to EVTOU5 Customers, *by Month*

Month	Climate Zone	Enrolled	Aggregate		Per-Customer		Ave. Daily Temp.
			Daily Ref. Load (MWh/h)	Daily Load Impact (MWh/h)	Daily Ref. Load (kWh/h)	Daily Load Impact (kWh/h)	
Oct-19	All	1,796	49.4	-0.4	27.5	-0.2	67
Nov-19	All	1,860	49.3	-4.4	26.5	-2.4	59
Dec-19	All	1,905	60.8	-3.1	31.9	-1.6	54
Jan-20	All	1,979	54.5	-4.4	27.5	-2.2	53
Feb-20	All	2,406	58.6	-6.4	24.4	-2.7	54
Mar-20	All	2,066	48.0	-3.1	23.2	-1.5	54
Apr-20	All	2,097	45.9	0.1	21.9	0.1	59
May-20	All	2,143	46.1	0.4	21.5	0.2	65
Jun-20	All	2,172	54.7	0.4	25.2	0.2	67
Jul-20	All	2,218	62.1	-2.3	28.0	-1.0	69
Aug-20	All	2,279	84.9	-3.1	37.2	-1.4	73
Sep-20	All	2,322	82.6	-2.9	35.6	-1.2	72

Figures 4.3 and 4.4 show aggregate hourly observed and estimated reference loads, along with hourly estimated load impacts for the customers that transitioned from EVTOU2 to EVTOU5 for the average weekday in August and January, respectively. The TOU peak periods are represented by the hours with blue highlighting. Both the summer and winter periods appear to exhibit load shifting from the TOU peak period to off-peak hours. Nearly all of the increased usage occurs in the morning hours, which corresponds with when the EVTOU5 rate is $0.11 per kWh less than the EVTOU2 rate.

Figure 4.3: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, August 2020*)

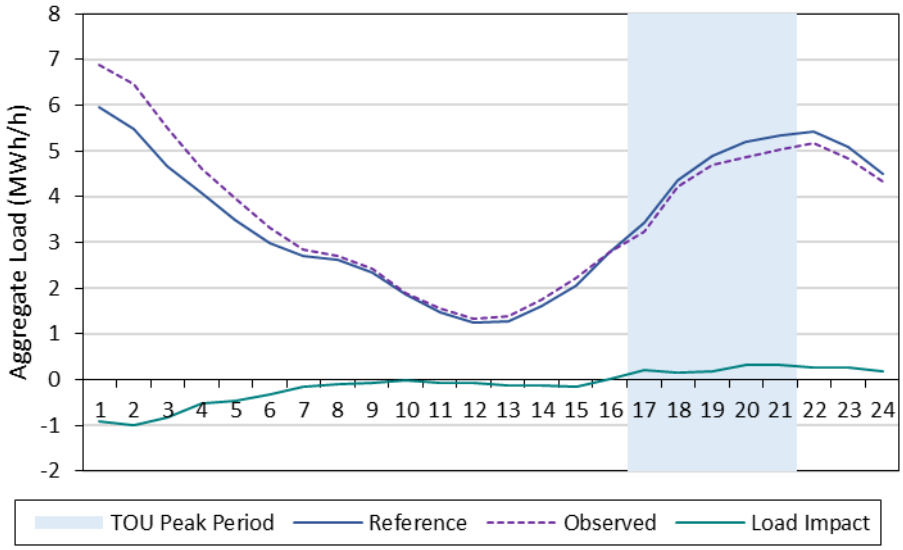
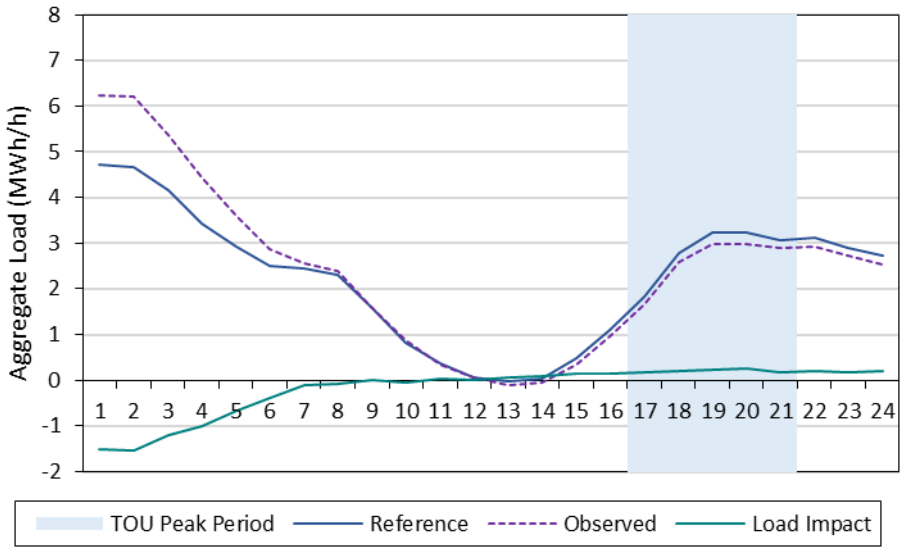


Figure 4.4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, January 2020*)



4.3 Ex-post TOU load impacts for EVTOU2 customers

This sub-section shows *ex-post* TOU load impact estimates for those customers enrolled in the EVTOU2 rate. Table 4.4 summarizes the average reference loads and TOU load impacts for the TOU peak period (*i.e.*, 4 p.m. to 9 p.m.), for the average weekday *by*

month, on an aggregate and per-customer basis. The months are shown starting with the first month included in the analysis (October 2019). The winter months are indicated by light blue shading. Enrollment slightly increased throughout the period, with the numbers of enrolled customers growing from 7,220 in October 2019 to 7,799 in September 2020.[24] The estimation methodology for EVTOU2 non-NEM customers included applying seasonal (March and April as a separate season) percentage load impacts to monthly reference loads. Similarly, seasonal *level* load impacts are used for NEM customers. Therefore, differences in percentage load impacts across seasons are driven by load impacts of NEM customers. The per-customer load impacts are largest during the summer months. The largest per-customer load impact of 0.22 kWh/h occurs in August, which also has the highest average event-hour temperature.

Table 4.4: TOU Peak Load Impacts for EVTOU2 Customers
– Average Weekday by Month

			Aggregate		Per-Customer		
Month	Climate Zone	Enrolled	Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	Ave. Temp.
Oct-19	All	7,220	10.29	1.21	1.43	0.17	71
Nov-19	All	7,244	10.49	0.49	1.45	0.07	60
Dec-19	All	7,280	12.27	0.55	1.68	0.08	56
Jan-20	All	7,403	10.97	0.50	1.48	0.07	56
Feb-20	All	7,462	10.02	0.48	1.34	0.06	57
Mar-20	All	7,528	9.40	0.96	1.25	0.13	57
Apr-20	All	7,562	9.20	1.01	1.22	0.13	63
May-20	All	7,605	8.59	0.53	1.13	0.07	69
Jun-20	All	7,655	9.70	1.38	1.27	0.18	72
Jul-20	All	7,702	11.12	1.49	1.44	0.19	74
Aug-20	All	7,719	15.44	1.67	2.00	0.22	78
Sep-20	All	7,799	15.02	1.60	1.93	0.21	78

Table 4.5 shows results by season and climate zone. The peak hour load impacts in the Inland climate zone are more than double those of the Coastal climate zone. Even with fewer customers, the Inland aggregate load impacts are larger.

[24] The enrollment numbers in the tables differ from the number of customers used in the regression models, which is a subset of customers that have all the required data for conducting the *ex-post* load impact analysis. Specifically, there were 394 incremental customers on the EVTOU2 rate with quality load data that were used in estimating the TOU load impacts. The aggregate TOU load impacts are then scaled to total enrollments.

Table 4.5: TOU Peak Load Impacts for EVTOU2 Customers
– Average Weekday by Season & Climate Zone

Season	Climate Zone	Enrolled (Average)	Aggregate		Per-Customer		Ave. Peak Temp.
			Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	
Summer	Coastal	5,337	8.45	0.72	1.58	0.13	73
	Inland	2,282	3.89	0.78	1.70	0.34	78
	All	**7,619**	**12.33**	**1.49**	**1.62**	**0.20**	**74**
Winter	Coastal	5,233	7.26	0.22	1.39	0.04	61
	Inland	2,208	2.85	0.41	1.29	0.18	58
	All	**7,441**	**10.11**	**0.63**	**1.36**	**0.08**	**60**

Table 4.6 shows the effect of EVTOU2 on average *daily* usage by month. EVTOU2 customers increased their energy consumption in all months except July through September. As will be shown below, the increase in usage occurs during the morning hours as customers shift charging their electric vehicles to that period. EVTOU2 customers exhibited an average per-customer increase of 1.27 kWh/h per day.

Table 4.6: TOU Average *Daily* Load Impacts for EVTOU2 Customers, *by Month*

Month	Climate Zone	Enrolled	Aggregate		Per-Customer		Ave. Daily Temp.
			Daily Ref. Load (MWh/h)	Daily Load Impact (MWh/h)	Daily Ref. Load (kWh/h)	Daily Load Impact (kWh/h)	
Oct-19	All	7,220	155.9	-3.8	21.6	-0.5	66
Nov-19	All	7,244	158.2	-15.2	21.8	-2.1	59
Dec-19	All	7,280	191.8	-15.5	26.4	-2.1	54
Jan-20	All	7,403	165.8	-16.2	22.4	-2.2	53
Feb-20	All	7,462	141.4	-16.8	19.0	-2.3	54
Mar-20	All	7,528	131.2	-19.2	17.4	-2.6	55
Apr-20	All	7,562	115.9	-15.7	15.3	-2.1	59
May-20	All	7,605	106.4	-13.1	14.0	-1.7	65
Jun-20	All	7,655	142.7	-0.7	18.6	-0.1	67
Jul-20	All	7,702	158.0	-0.4	20.5	0.0	69
Aug-20	All	7,719	224.7	1.3	29.1	0.2	73
Sep-20	All	7,799	207.6	0.5	26.6	0.1	72

Figure 4.5 shows aggregate hourly observed and estimated reference loads, along with hourly estimated TOU load impacts for EVTOU2 customers for the average weekday in August. Figure 4.6 shows the same information for the average weekday in January. The hourly TOU load impacts in August illustrate a reduction in load during the peak hours as

well as during a portion of the partial peak hours (*i.e.,* HE 10-16 and HE 22-24). The greatest decrease in usage occurs during the peak period. The peak period reduction is lower during January. In each month, there is a significant increase in usage during the super off-peak hours when the rate is lowest. This suggests that customers may shift electric vehicle charging from the afternoon to morning hours.

Figure 4.5: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 Customers (*Average Weekday, August 2020*)

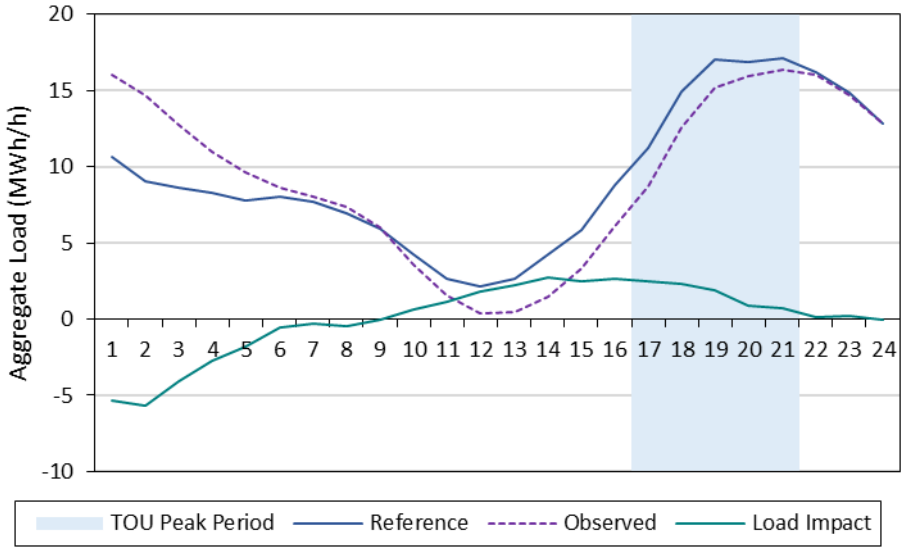
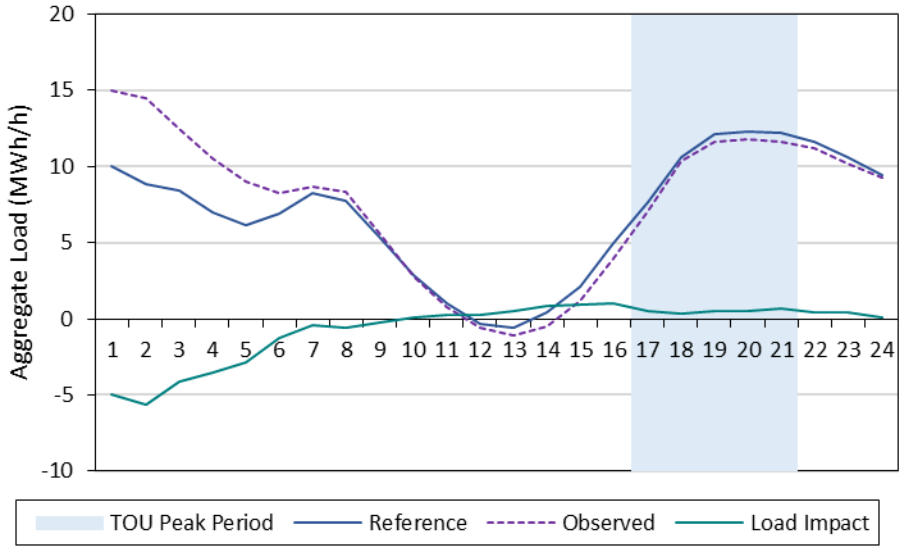


Figure 4.6: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 Customers (*Average Weekday, January 2020*)



4.4 Ex-post TOU load impacts for EVTOU5 customers

This sub-section shows *ex-post* TOU load impact estimates for those customers enrolled in the EVTOU5 rate. Table 4.7 summarizes the average reference loads and TOU load impacts for the EVTOU peak period (*i.e.*, 4 p.m. to 9 p.m.), for the average weekday *by month*, on an aggregate and per-customer basis. The months are shown starting with the first month included in the analysis (October 2019). The winter months are indicated by light blue shading. Enrollment additions continued throughout the period, with the numbers of enrolled customers rising from 7,330 in October 2019 to 11,186 in September 2020.[25] The per-customer load impacts are positive across all seasons.[26] The largest per-customer load impact of 0.33 kWh/h occurs in August.

Table 4.7: TOU Peak Load Impacts for EVTOU5 Customers
– Average Weekday by Month

			Aggregate		Per-Customer		
Month	Climate Zone	Enrolled	Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	Ave. Temp.
Oct-19	All	7,330	9.69	1.94	1.32	0.26	71
Nov-19	All	7,695	11.13	2.09	1.45	0.27	60
Dec-19	All	8,121	13.56	2.35	1.67	0.29	56
Jan-20	All	8,763	12.89	2.42	1.47	0.28	56
Feb-20	All	9,173	12.24	2.46	1.33	0.27	57
Mar-20	All	9,559	10.94	1.98	1.14	0.21	57
Apr-20	All	9,838	11.30	2.11	1.15	0.21	63
May-20	All	10,040	11.95	2.81	1.19	0.28	70
Jun-20	All	10,280	12.33	2.83	1.20	0.28	72
Jul-20	All	10,568	14.53	3.08	1.37	0.29	74
Aug-20	All	10,867	21.02	3.56	1.93	0.33	78
Sep-20	All	11,186	21.08	3.50	1.88	0.31	78

Table 4.8 shows results by season and climate zone. The Coastal climate zone has nearly twice the number of enrolled customers. During the summer period, the average per-customer load impact and temperature was higher for the Inland climate zone at 0.43

[25] The enrollment numbers in the tables differ from the number of customers used in the regression models, which is a subset of customers that have all the required data for conducting the *ex-post* load impact analysis. Specifically, there were 2,560 incremental customers on the EVTOU5 rate with quality load data that were used in estimating the TOU load impacts. The aggregate TOU load impacts are then scaled to total enrollments.

[26] The estimation methodology for EVTOU non-NEM customers included applying seasonal (March and April as a separate season) percentage load impacts to monthly reference loads. Similarly, the seasonal *level* load impacts are used for NEM customers. Therefore, differences in percentage load impacts across seasons is driven by load impacts of NEM customers.

kWh/h and 78 degrees Fahrenheit. The per-customer winter load impacts are similar between climate zones. Aggregate load impacts are greater in the Coastal climate zone during both seasons because of the differences in enrollment numbers.

Table 4.8: TOU Peak Load Impacts for EVTOU5 Customers
– Average Weekday by Season & Climate Zone

Season	Climate Zone	Enrolled (Average)	Aggregate		Per-Customer		Ave. Temp.
			Peak Ref. Load (MWh/h)	Peak Load Impact (MWh/h)	Peak Ref. Load (kWh/h)	Peak Load Impact (kWh/h)	
Summer	Coastal	6,657	10.08	1.65	1.51	0.25	73
	Inland	3,389	5.77	1.46	1.70	0.43	78
	All	**10,046**	**15.86**	**3.11**	**1.58**	**0.31**	**75**
Winter	Coastal	5,999	8.36	1.64	1.39	0.27	61
	Inland	3,028	3.56	0.59	1.18	0.20	59
	All	**9,027**	**11.92**	**2.23**	**1.32**	**0.25**	**60**

Table 4.9 shows the effect of EVTOU5 on average *daily* usage by month. EVTOU5 customers *increased* their energy consumption during all months. The overall change was an average annual *increase* of 1.27 kWh per-day, or 6 percent. The increased energy occurs during the morning hours.

Table 4.9: TOU Average *Daily* Load Impacts for EVTOU5 Customers, *by Month*

Month	Climate Zone	Enrolled	Aggregate		Per-Customer		Ave. Daily Temp.
			Daily Ref. Load (MWh/h)	Daily Load Impact (MWh/h)	Daily Ref. Load (kWh/h)	Daily Load Impact (kWh/h)	
Oct-19	All	7,330	168.0	-16.0	22.9	-2.2	66
Nov-19	All	7,695	196.0	-8.5	25.5	-1.1	59
Dec-19	All	8,121	241.5	-8.3	29.7	-1.0	54
Jan-20	All	8,763	229.9	-10.3	26.2	-1.2	53
Feb-20	All	9,173	211.0	-11.8	23.0	-1.3	54
Mar-20	All	9,559	190.9	-19.0	20.0	-2.0	54
Apr-20	All	9,838	166.8	-13.1	17.0	-1.3	59
May-20	All	10,040	171.6	-3.2	17.1	-0.3	65
Jun-20	All	10,280	201.0	-14.0	19.5	-1.4	67
Jul-20	All	10,568	231.9	-13.9	21.9	-1.3	69
Aug-20	All	10,867	337.0	-11.8	31.0	-1.1	73
Sep-20	All	11,186	323.9	-13.4	29.0	-1.2	72

Figure 4.7 shows aggregate hourly observed and estimated reference loads, along with hourly estimated TOU load impacts for the EVTOU5 customers for the average weekday in August. Similarly, Figure 4.8 illustrates loads and load impacts for the average weekday in January. The hourly TOU load impacts in August demonstrate a reduction in load during the peak hours as well as during a portion of the partial peak hours (*i.e.,* HE 7-16 and HE 22-24). The greatest decrease in usage for EVTOU5 customers occurs during the peak period (and like EVTOU2 customers) significant load shifting to non-peak hours exists during super off-peak hours. The greatest increase in usage occurs during the morning hours when an electric vehicle is likely programed to begin charging. For example, the usage increase during the August morning hours (HE 1-7) indicates a 48 percent increase in usage.

Figure 4.7: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, August 2020*)

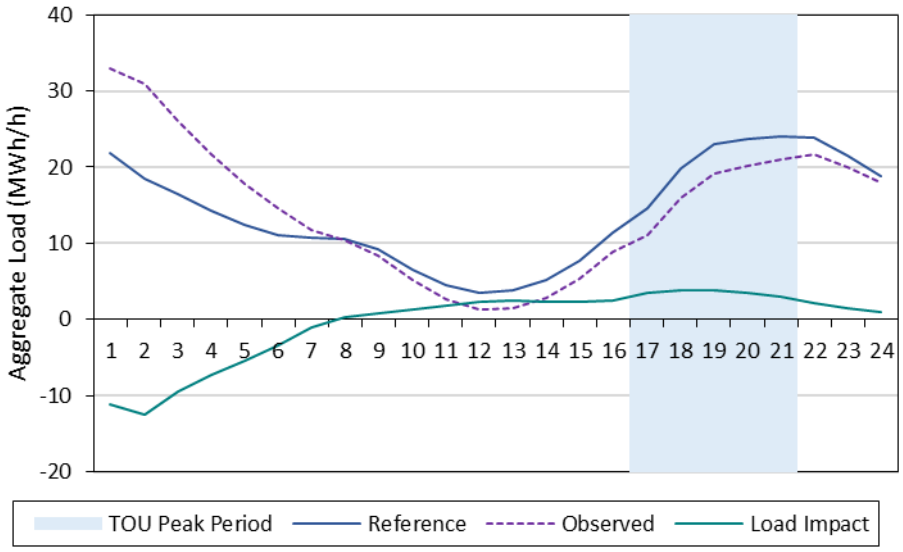
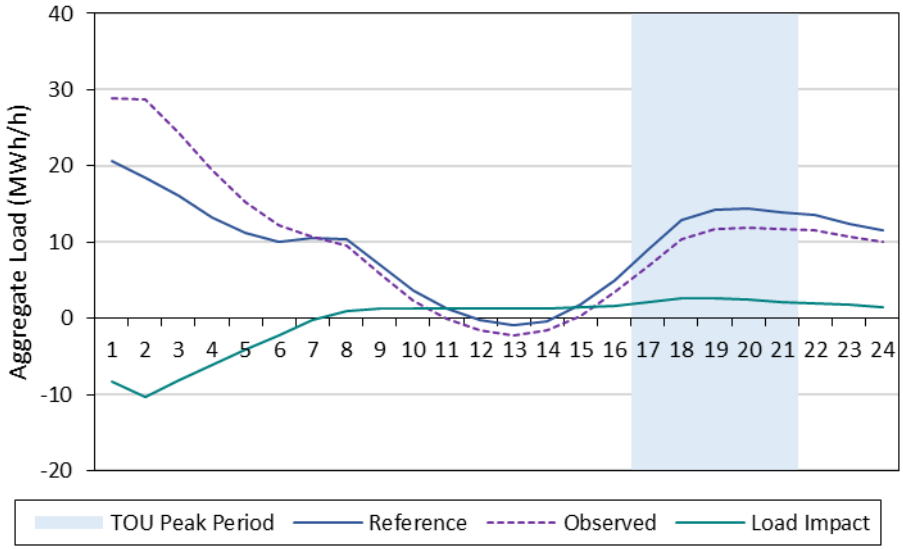


Figure 4.8: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, January 2020*)



5. VGI Pilot Evaluation Study Findings

This section presents summaries and results for the VGI pilot. Table 5.1 presents session-level summary statistics between work and "home" stations over the period October 2018 through September 2020. Results for VGI facilities at work locations are further bifurcated by who pays the rate (Rate to Host, Rate to Driver). Note the comparatively low number of EV drivers relative to the number of sessions for the work / rate-to-host category (the leftmost column of results). This appears to reflect fleet charging, where multiple vehicles / drivers are associated with a single EV driver ID. The number of overall stations and total drivers increased in PY20. Specifically, the number of stations increased from 2,066 to 2,269 while the number of drivers increased from 1,135 to 1,542. The number of total sessions at work, however, decreased from 162,549 to 129,663 as a result of the Covid-19 pandemic. The number of home charging sessions increased from 35,466 to 50,306.

Table 5.1 VGI Pilot Summary Statistics

Characteristics	Work		Home
	Rate to Host	Rate to Driver	Rate to Driver
Stations	696	972	601
EV Drivers	31	1,058	453
Sessions	79,713	49,950	50,306
Avg Start Time	7.46	8.77	9.11
	(5.06)	(3.59)	(8.50)
Avg Duration (hours)	8.55	5.88	8.07
	(7.23)	(3.93)	(6.50)
Avg kWh	9.75	10.45	8.52
	(10.34)	(9.56)	(11.30)
Avg Price	0.19	0.18	0.19
	(0.13)	(0.11)	(0.13)

Note: Standard errors in parentheses.

The Covid-19 pandemic had a large impact on the frequency of charging electric vehicles and, consequently, the energy demanded. Figure 5.1 illustrates the aggregate energy consumed by customers in the VGI pilot since October of 2017. There is a sharp decline in energy at the beginning of the Covid-19 pandemic in March 2020. The reduction is greatest for the workplace stations while there is only a slight decrease for at-home charging. The energy demanded has slightly increased after the decline at the beginning of the pandemic, however, workplace demand isn't near pre-Covid levels. The pattern is also representative of the frequency and duration of charging as well as the number of stations being used.

Figure 5.1: Aggregate VGI Energy Consumed Over Time

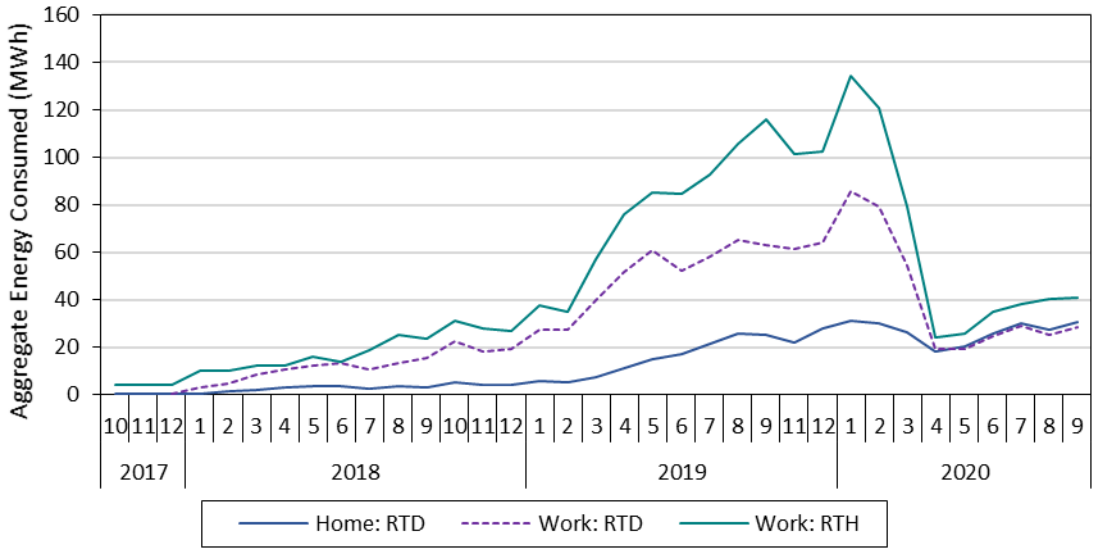


Figure 5.2 illustrates the number of unique drivers over time since October 2017. The work / rate-to-host drivers are shown on the secondary axis since their numbers are relatively low (but their aggregate demand is the greatest). The work / rate-to-driver exhibited the largest decrease while the remaining two categories remained relatively consistent.

Figure 5.2: Unique VGI Driver Counts Over Time

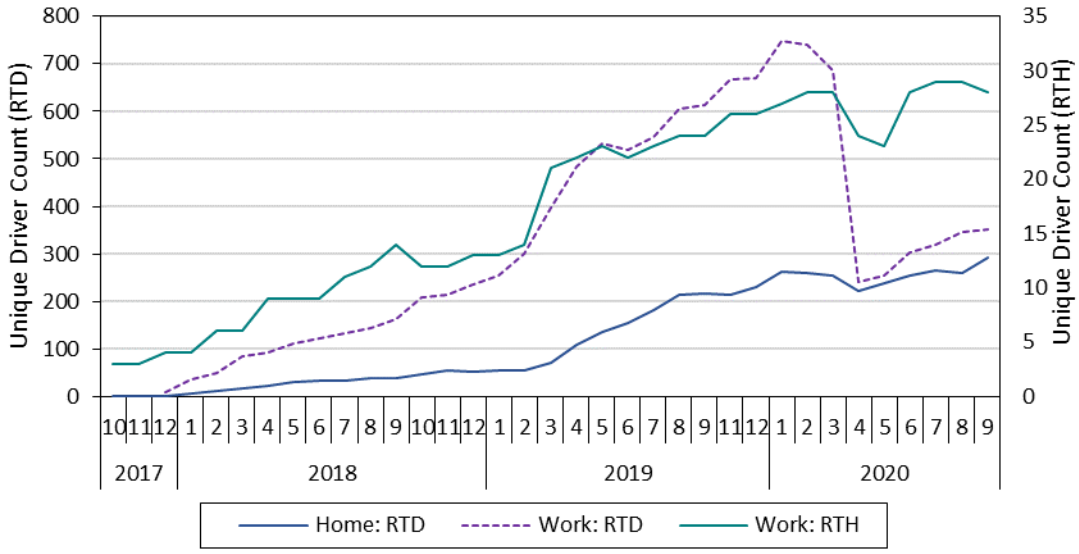


Figure 5.3 illustrates the distribution of session charge start times by VGI facility/payment type. Vehicles that are plugged into the home facilities have over 40 percent of charge times starting in the first hour of the day. Most of the remaining home start times are geared toward the evening hours. Work charging, on the other

hand, is more likely to occur during the mid-morning, with the greatest proportion of sessions beginning in hour-ending eight. The rate-to-host charging also has a significant portion of sessions beginning at the end of the day, while rate-to-driver workstations are relatively less likely to begin at night.

Figure 5.3: Distribution of VGI Pilot Charging Start Hours

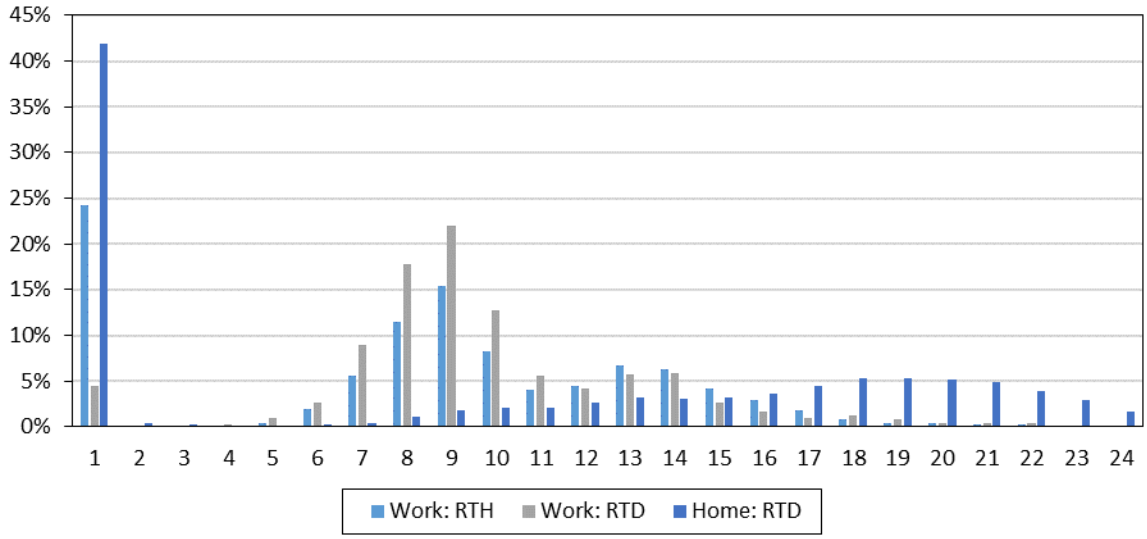
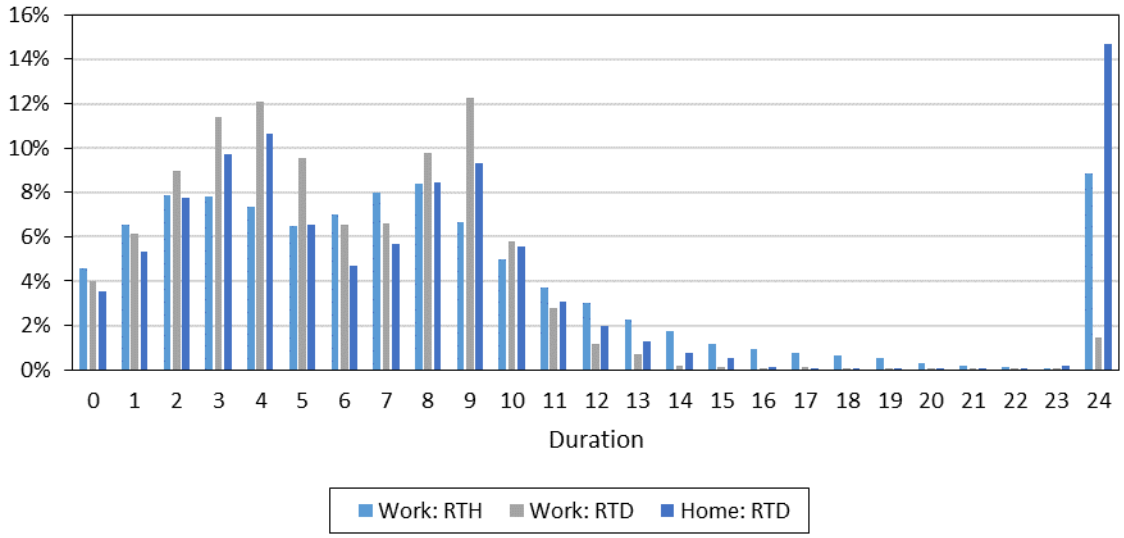


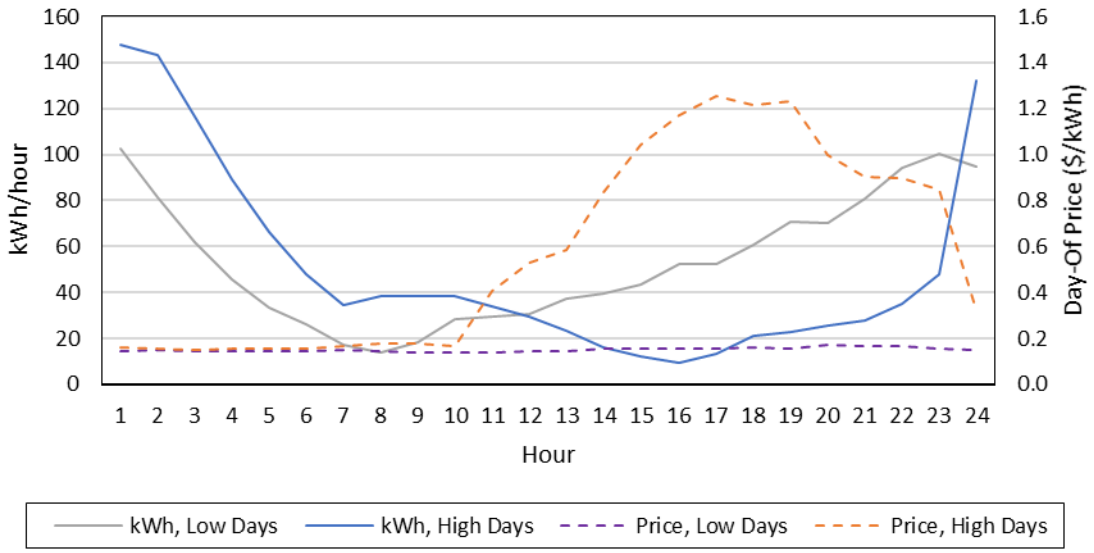
Figure 5.4 shows the frequency distribution of session duration, separated by charging location and who pays. It appears that work / rate-to-host sessions have the highest share of short-duration sessions (two hours or less), while home charging sessions are most likely to last a full 24 hours.

Figure 5.4: Distribution of VGI Pilot Session Total Duration



To examine the effect of pricing on EV charging behavior, we focused on key non-holiday weekdays in August 2020. During the early part of the month VGI prices were quite low, averaging $0.15 per kWh and never exceeding $0.30 per kWh.[27] Conditions changed dramatically in the middle of the month, causing prices to increase to an average of approximately $0.60 per kWh and a maximum price of $2.11 per kWh.[28] Figures 5.5 through 5.7 show the average prices and total EV charging station usage during those low- and high-priced days, separated by home charging customers, workplace RTD charging, and workplace RTH charging.

Figure 5.5: August 2020 Low vs High Price Days, Home: RTD



[27] The average session price of $0.15 accounts for 70 percent of all sessions. The distribution of average session prices follows a normal distribution pattern with 93 percent of sessions containing the average price between $0.10 and $0.20.

[28] The low-priced days we used are: 8/3 to 8/7 and 8/10 to 8/12. The high-priced days we used are: 8/17 to 8/21 and 8/24 to 8/27.

Figure 5.6: August 2020 Low vs High Price Days, Work: RTD

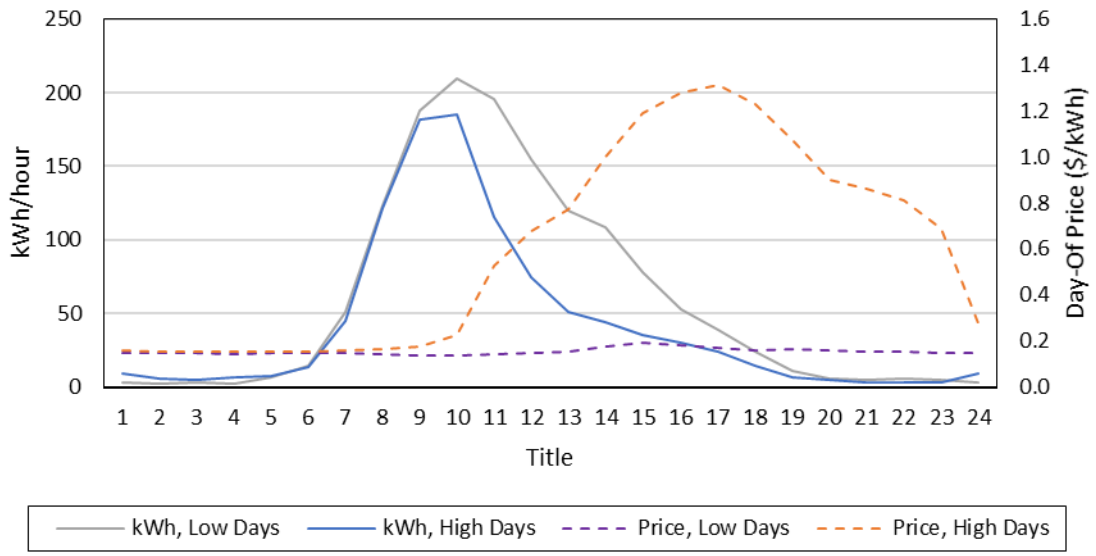


Figure 5.7: August 2020 Low vs High Price Days, Work: RTH

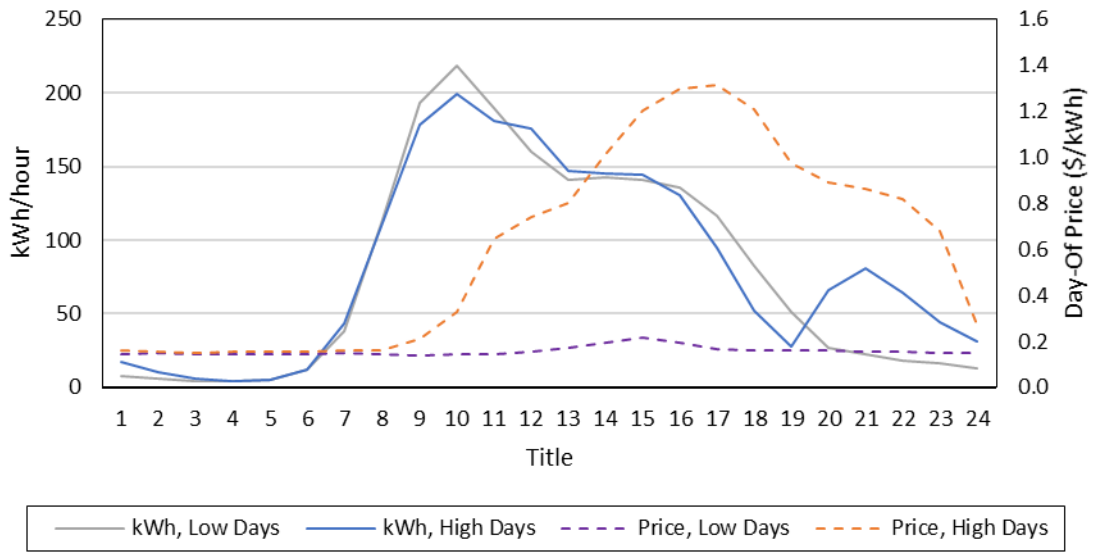


Figure 5.5 versus Figures 5.6 and 5.7 illustrates that Home charging has a different hourly pattern than workplace charging, with a higher share of charging during the overnight hours. The workplace charging is highest during the morning hours, presumably following the arrival of employees at their place of work.

On the high-priced days, VGI prices don't significantly increase until the late morning hours and reach their peak at about 5 p.m. On the low-priced days, VGI prices display very little variation across the hours of the day. EV charging kWh is reduced when VGI prices are higher and the customer pays. For home charging customers (Figure 5.5), the

reductions are focused in the afternoon and early evening hours. For workplace charging (Figures 5.6), the decreases occur earlier in the day. EV charging behavior does not appear to be affected by high prices when the host pays the rate. For instance, Figure 5.7 shows an overall charging pattern for workplace RTH charging, but the usage on the high- and low-priced days is very similar.

The timing of the load impacts suggests a higher reliability value for the application of VGI to home charging, as there are significant load impacts during the RA window (HE17 to 21). In contrast, the workplace RTD load impacts, while significant in magnitude, are concentrated much earlier in the day (peaking from HE11 to 14). These findings suggest that VGI pricing can be an effective means of reducing EV charging during system emergencies or when capacity margins are low.

Table 5.2 presents the estimates from the session-level regression models described in Section 3.4. This analysis provides details regarding customer behavior at the session level. The estimates of primary interest are in the first two rows, showing the effect of variations in the price per kWh on the total kWh of the charging session (in the first set of columns) and the duration of the charging session (in the two rightmost columns of the table). The "Home" columns show that higher electricity prices are associated with lower kWh totals (the -5.660 coefficient indicates that a $0.10 per kWh increase in price leads to a 0.566 kWh reduction in energy charged during the session), and shorter charging durations.

In contrast, the "Work" estimates show a *positive* price effect for rate-to-host charging sessions (the 2.404 kWh estimate and the 1.614 duration estimate), but a negative price effect in the kWh model for rate-to-driver sessions. The total effect for rate-to-driver sessions is the sum of the "Actual Price" and "Actual Price X RTD" estimates, or 2.404 + (-6.087) = -3.683. This means that a $0.10 per kWh increase in price reduces charged kWh by 0.3683. The duration model for workplace sessions indicates that the price effect is reduced for rate-to-driver sessions, as the coefficient is -0.571 and statistically significant.

The kWh models reflect interesting and intuitively appealing results: EV customers who pay for the charging session are sensitive to the electricity price, while EV customers who do not pay for the charging session are not. It is somewhat odd that this result is not also reflected in the duration models, as one might expect that reduced kWh occurs via earlier disconnections. As was shown previously, the Covid-19 resulted in a reduction of aggregate energy demand and number of charging sessions. For the charging sessions that still occurred during the pandemic, Table 5.2 indicates that the usage and duration increased slightly (the at-home result is not statistically significant); possibly a result of customers not needing to drive as much during the pandemic and consequently leaving their vehicles to charge for longer.

Table 5.2: VGI Regression Results

Variable	kWh		Duration	
	Work	Home	Work	Home
Actual Price ($)	2.404***	-5.660***	1.614***	-0.331***
	(0.000)	(0.000)	(0.000)	(0.046)
Actual Price X RTD	-6.087***	n/a	-0.571**	n/a
	(0.000)		(0.028)	
Mean 17	-0.031***	0.025**	-0.019***	0.006
	(0.000)	(0.044)	(0.000)	(0.189)
		0		
Covid-19	0.517***	0.046	0.256***	1.221***
	(0.001)	(0.873)	(0.000)	(0.000)
Start Hour FE	Y	Y	Y	Y
Driver FE	Y	Y	Y	Y
Station FE	Y	Y	Y	Y
Observations	259,051	56,608	259,051	56,608
R-squared	0.318	0.367	0.343	0.518

Robust p-value in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6. *Ex-Ante* Evaluation Methodology

This section describes the development and methodologies used of *ex-ante* load impact forecasts for both electric vehicle rates. *Ex-ante* TOU load impacts are not provided for the customers who switch from EVTOU2 to EVTOU5 or for customers in the VGI pilot.[29]

Ex-ante load impacts represent forecasts of load impacts that are expected to occur in TOU peak periods, under standardized weather conditions. The forecasts are based on

[29] Our analysis of VGI is somewhat unconventional as it does not lend itself well to Protocols-style reporting, for a few reasons. First, VGI prices change each hour with system conditions, whereas most evaluations are of rates with a pre-determined schedule (*e.g.*, a time-of-use rate) or an event-based rate (*e.g.*, either a price-based rate like Critical Peak Pricing or a curtailable rate like an air conditioning load control program). Second, the notion of a "customer" in VGI is somewhat more complicated than it is for other programs. A customer can be an EV owner who has sporadic charging sessions, or a charging station, or perhaps a facility with multiple charging stations. Charging stations are not continuously in use during our sample period. Most dramatically, the number of workplace chargers in use reduced by about two thirds in mid-March, presumably due to COVID effects. Third, the counterfactual for the load impact estimate is somewhat more complicated than it is for other programs. There's no tariff-based comparison as one would have in a TOU study; and there's not a strict event vs. non-event difference as there is in CPP.

Our simple comparison of high and low-price day outcomes during a relatively short span of time is an effective means of alleviating these concerns (see Figures 5.5 through 5.7). By focusing on aggregate EV charging load by date and category (home vs. workplace, RTD vs. RTH) over a relatively short period of time, we avoid complications that arise from large changes in individual station use over time. By focusing on a small set of low- and high-priced days, we have constructed a scenario that represents the value of the program during extreme circumstances.

analyses of per-customer load impact findings from *ex-post* evaluations, development of weather-sensitive reference loads, and incorporation of utility forecasts of program enrollments.

In PY2020, the COVID-19 pandemic influenced customer reference loads and load impacts. The following primary sections provide details regarding a standard *ex-ante* methodology while Section 6.4 provides additional methods and adjustments used to account for COVID-19 during the forecast period.

6.1 Per-customer load impacts

To calculate TOU load impacts for EVTOU2 and EVTOU5 customers, seasonal percentage peak load impacts from the *ex-post* analysis are applied to weather-sensitive reference loads that are developed as described in the following sub-section.

NEM customer reference loads and load impacts are estimated separately from non-NEM customers. *Ex-post* seasonal level TOU load impacts are applied to reference loads and scaled to the count of enrolled customers. The proportion of NEM customers is assumed to remain constant throughout the forecast period. Non-NEM and NEM results are customer weighted to produce program TOU outcomes.

6.2 Per-customer reference loads

Weather-sensitive reference loads for the average customer in each of the two climate zones were developed through a regression analysis of hourly load data for weekday non-event days for customers on both rates.[30] Customers are first sorted as weather sensitive or not.[31] Regression models were estimated separately for each hour of the day, by weather sensitivity, using daily observations for weekdays, and a form similar to

[30] The most recent October through September period is used. In the current PY20 analysis, however, the COVID-19 pandemic influenced reference loads. Therefore, PY19 reference loads are used as a baseline and COVID-19 adjustments are incorporated over the forecast period. The COVID-19 assumptions and reference load adjustments are described below in Section 6.4.

[31] Customer-specific regressions are implemented to categorize customers as weather sensitive or not. Weather sensitive customers change usage in response to changes in the weather, while non-weather sensitive customers do not. Determining which customers are non-weather sensitive allows for a more parsimonious regression model by not including weather variables as explanatory variables for these customers. The following regression specification is used to determine whether a customer is weather sensitive:

$$Q_t = b^{Weather} \times Weather_t + \sum_{i=2}^{5}\left(b_i^{DTYPE} \times DTYPE_{i,t}\right) + \sum_{i=7}^{9}\left(b_i^{MONTH} \times MONTH_{i,t}\right) + \sum_{i=1}^{EVT}\left(b_i^{EVT} \times EVT_{i,t}\right) + e_t$$

, where Q_t represents the average customer usage during event hours on day t in the summer months of June through September. $DTYPE_{i,t}$ represents the day of week, while $MONTH_{i,t}$ represents each month. The $EVT_{i,t}$ variables control for any event days a customer faces (BIP, CPP, etc.). The variable of importance is $Weather_t$, which is defined as CDD55, CDD60, or CDD65, each as a separate regression. The regression is estimated for each customer and weather specification. A customer is identified as weather sensitive if the weather coefficient ($b^{Weather}$) is positive and statistically significant for any of the three separate weather specifications.

that of the *ex-post* load impact models. The primary differences between this analysis compared to the *ex-post* analysis are:

- The analysis included only the treatment customers;
- Weather variables were included (Mean17, CDD65, HDD65, and HDH65)[32];
- Data for all months were included, rather than estimating separate models by month or season; and
- Month-year indicator variables were added to account for monthly and yearly differences in usage patterns.

The resulting equations allow the simulation of "observed" (*i.e.*, post EVTOU load impacts) loads under the four different weather scenarios. Reference loads for the alternative scenarios were then obtained by adjusting the above observed loads by the relevant estimated percentage EVTOU load impacts from the *ex-post* analysis.[33] For NEM customers, reference loads are calculated by adjusting observed loads by the relevant seasonal *ex-post* level load impacts. The process for obtaining simulated reference and observed loads is completed separately for each rate.

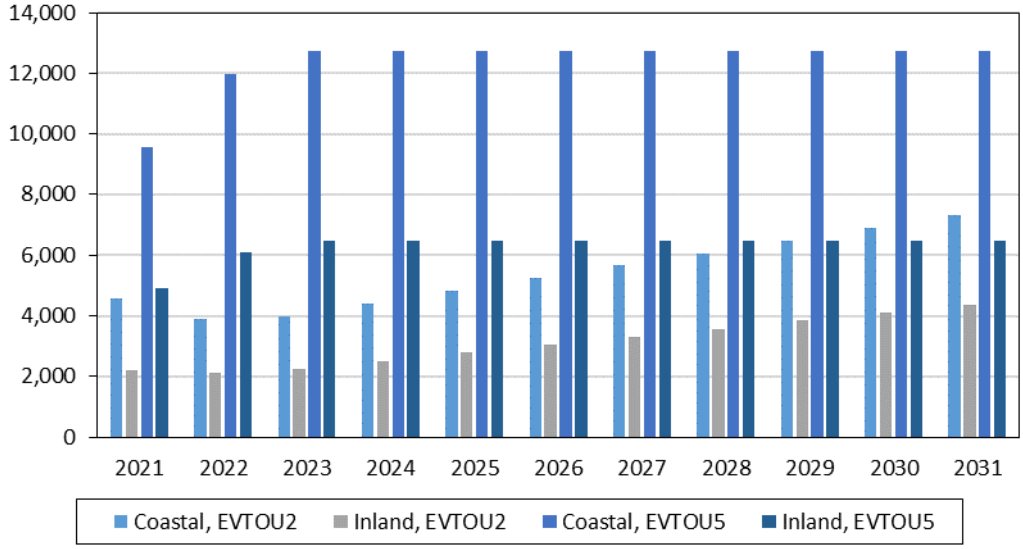
6.3 Enrollment forecast

Per-customer reference loads and loads impacts are scaled to program levels based on the number of enrolled customers. Figure 6.1 shows SDG&E's enrollment forecasts for the EVTOU2 and EVTOU5 rates. Enrollment is anticipated to decrease slightly until 2023 for EVTOU2 customers. Afterwards, EVTOU2 enrollment is forecasted to increase until nearly doubled by the end of the forecast period. The proportion of inland EVTOU2 customers slightly increases over time from 32 to 37 percent. Enrollment in EVTOU5 is forecasted to increase 33 percent by 2033 and then remain steady thereafter. The aggregate EVTOU5 load impact is expected to be greater in the Coastal climate zone than in the Inland because of twice the number of enrolled customers.

[32] Mean17 is the average temperature in degrees Fahrenheit during the first 17 hours of the day. Cooling degree days (CDD) for day are defined as: CDD65 = max(0,((Day Maximum Temperature – Day Minimum Temperature in °F)/2) – 65). Likewise, heating degree days (HDD) for day are defined as: HDD65 = max(0,65 – ((Day Maximum Temperature – Day Minimum Temperature in °F)/2)). Heating degree hours (HDH) for each hour of the day are defined as: HDH65 =max(0, 65 – Temperature in °F).

[33] The adjustment takes the form of Reference = Observed / (1 - %TOULoadImpact). CA Energy Consulting examined several alternative approaches to developing the weather-sensitive reference load, including the same type of regression analysis using load data for the matched control group customers. The resulting reference loads were not very sensitive to the data and approach used, although the selected approach produced more accurate loads during the swing months.

Figure 6.1: Enrollments in EVTOU Rates



6.4 COVID-19 Adjustments to the Ex-Ante Forecast

Residential customers, on average, exhibited an increase in load as a response to the COVID-19 pandemic which began in March 2020. EV customers, additionally, exhibited a reduction in electric vehicle charging during the overnight hours. As a result, the methodology described above for estimating *ex-ante* reference loads and load impacts requires an adjustment to account for how COVID will affect customer usage over the forecast period. First, we estimate the effect COVID had on the average customer's hourly reference loads. Separate hourly COVID effects are estimated by rate (EVTOU2 and EVTOU5) and NEM status. Second, we adjust the magnitude of the COVID effect over time based on utility-provided assumptions regarding the expected evolution of the COVID effect during the forecast period. Consequently, the EVTOU load impacts are adjusted for non-NEM customers because they are calculated based upon the *ex-post* load impact percentage relative to the reference load. Third, EVTOU load impacts for NEM customers are adjusted based upon the difference between the PY20 and PY19 load impacts and the assumed transition of the COVID effect over time.[34]

The following regression specification is estimated for each rate, by NEM status, and hour separately to capture the effect COVID had on consumption:

$$kWh_{c,d} = \beta_0 + \beta_1 \times COVID_d + \beta_2 \times CDD65_d + \beta_3 \times HDD65_d + \Sigma_m (\beta_{4,m} \times MONTH_{d,m}) + \Sigma_{Cust} (\beta_{5,Cust} \times C_c) + \varepsilon_{c,d}$$

[34] The EVTOU load impacts for NEM customers are not based on percentages relative to the reference load. The *ex-ante* load impact, consequently, would not differ as a result of COVID-19 adjustments to reference loads. The assumption is made that differences between the PY20 and PY19 *ex-post* level load impacts for NEM customers is a result of COVID-19. The magnitude of the COVID effect on NEM *ex-ante* load impacts decreases over time based on the assumed timeline provided by SDG&E.

Table 6.1: Descriptions of Terms included in the COVID Regression Equation

Variable Name	Variable Description
$kWh_{c,d}$	Load in a particular hour for customer *c* on date *d*
The various *b*'s	the estimated parameters
$COVID_d$	an indicator variable for if day *d* is during the COVID-19 pandemic (*i.e,* post March 2020)
$CDD65_d$	average cooling degree days[35]
$HDD65_d$	average heating degree days[36]
$MONTH_d$	a series of indicator variables for each month
C_c	Variable indicating that the observation is associated with customer *c*
$\varepsilon_{c,d}$	the error term

Table 6.1 provides a description of the variables in the model. Customer non-holiday weekday load data covering the period October 2018 through September 2020 is used to provide sufficient pre-COVID information.[37] Only embedded customers, *i.e.,* those that were on the EVTOU rate for the entire period are included to prevent confounding the COVID effect with an EVTOU effect. The variable of importance, *COVID*, provides an estimate of each customer's load change in response to the pandemic. The estimated coefficient for *COVID*, β_1, is used to adjust *ex-ante* reference loads for the various levels of COVID specified in the utility's forecasts.

Figures 6.2 through 6.5 illustrate the average per-customer August *ex-ante* reference loads with and without COVID for each rate (EVTOU2 and EVTOU5) and NEM status. The purple dashed line displays the adjusted reference loads assuming 100% of the COVID effect. In each case, energy consumption is greater during the day as a result of COVID. The morning hours, however, display a reduction in energy use as customers likely drive less, resulting in reduced charging of their electric vehicles. For example, the average EVTOU2 non-NEM customer decreased usage by 18 percent during the morning hours (hour-ending 1-8), but increased usage by 7 percent during the remaining hours of the day.

[35] Cooling degree days (CDD) are defined as MAX[0, (Max Temp + Min Temp) / 2 – 60], where Max Temp is the daily maximum temperature in degrees Fahrenheit and Min Temp is the daily minimum temperature. Customer-specific CDD values are calculated using data from the most appropriate weather station.

[36] Heating degree days (HDD) are defined as MAX[0, 60 – (Max Temp + Min Temp) / 2], where Max Temp is the daily maximum temperature in degrees Fahrenheit and Min Temp is the daily minimum temperature. Customer-specific HDD values are calculated using data from the most appropriate weather station.

[37] A greater period of data is required to not confound the COVID effect with usage that occurs during summer months. Therefore, it is important to have at least a full year of data before the pandemic began in March 2020. The maximum amount of data available is used for customers that had less than the full two-year period. Specific days that have an effect on customer usage are removed from the analysis (*e.g.,* program events, public safety power shutoffs, FLEX alert).

Figure 6.2: *Ex-Ante* August Load with Covid-19 Adjustment, EVTOU2 non-NEM Customers

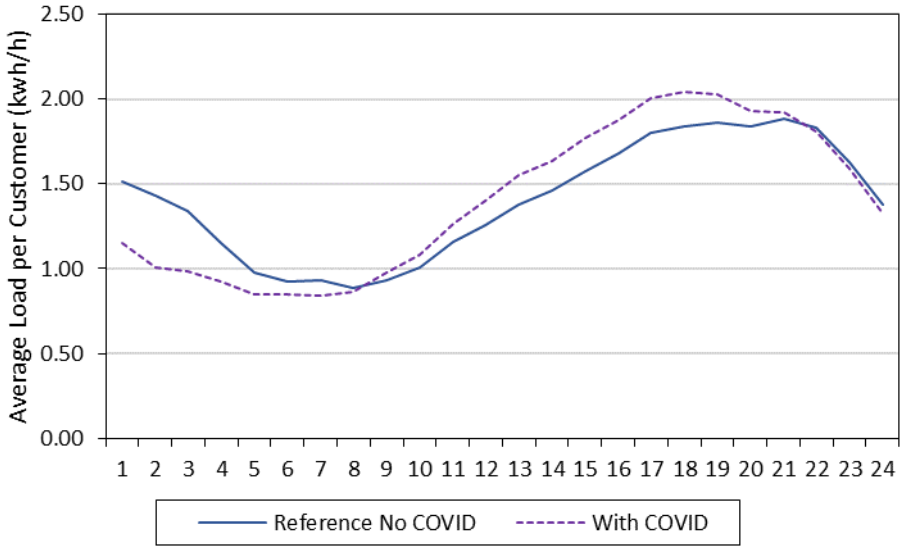


Figure 6.3: *Ex-Ante* August Load with Covid-19 Adjustment, EVTOU2 NEM Customers

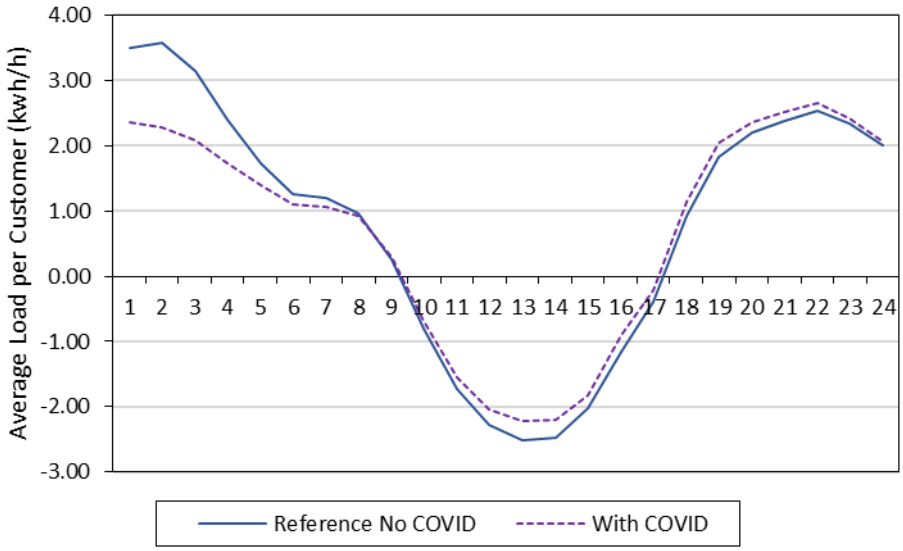


Figure 6.4: *Ex-Ante* Aggregate June Load with Covid-19 Adjustment, EVTOU5 non-NEM Customers

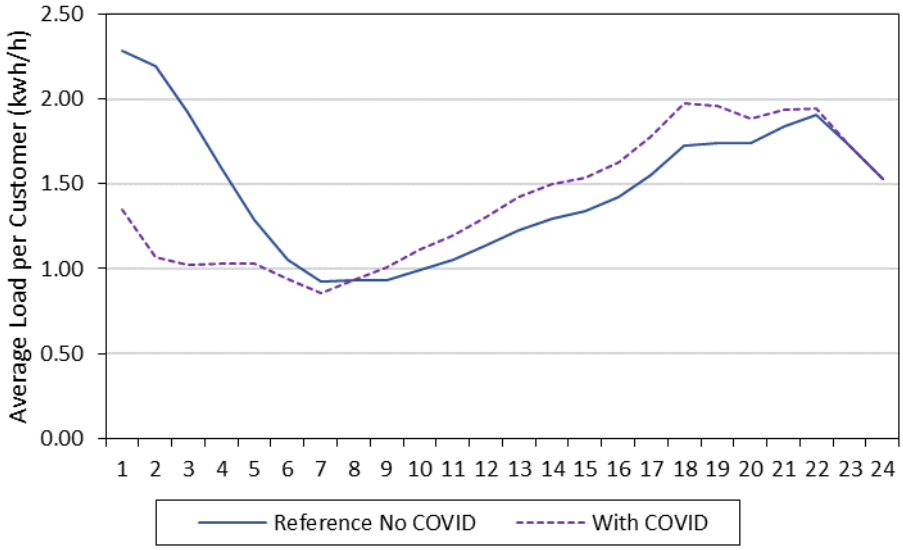
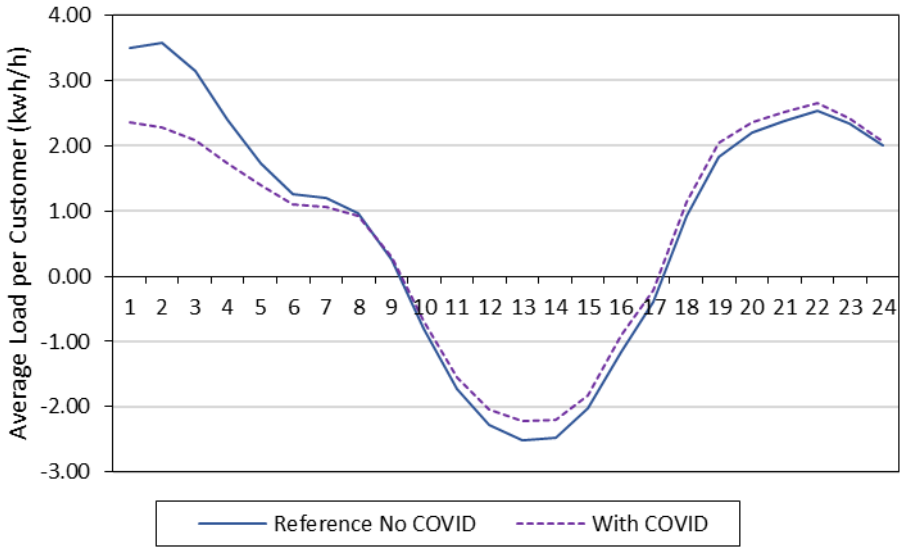


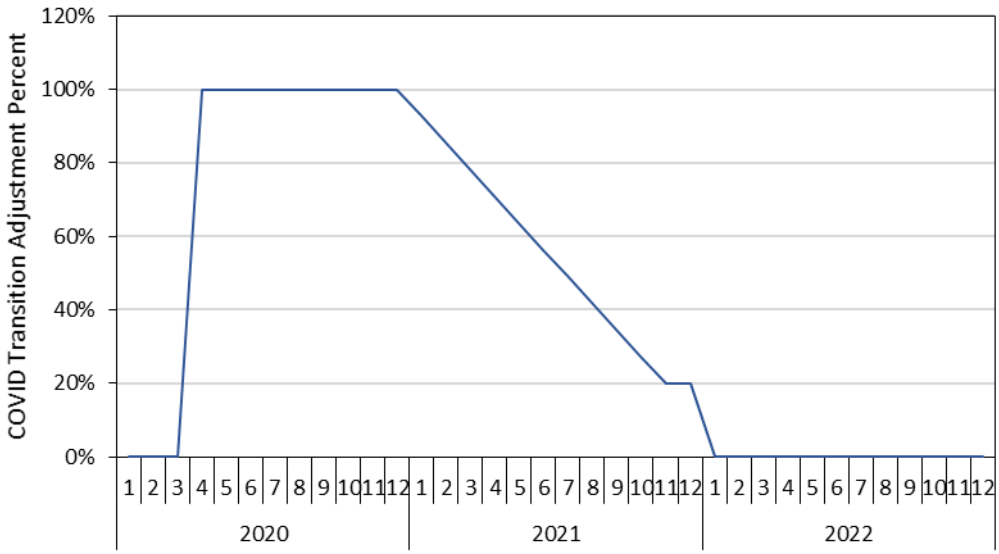
Figure 6.5: *Ex-Ante* Aggregate June Load with Covid-19 Adjustment, EVTOU5 non-NEM Customers



SDG&E provided assumptions regarding how to adjust the magnitude of the COVID effect over time. The magnitude of the pandemic effect on customer usage lessens over time. Therefore, COVID-affected reference loads (and load impacts) will approach the non-COVID reference load according to the COVID transition assumptions. Figure 6.6 illustrates the monthly COVID transition assumption, with the effect assumed to be zero percent starting in 2022. The percentage assumptions are applied to the magnitude of the COVID effect in its respective period. For example, a 0.1 kW COVID related usage

decrease is reduced to 0.05 kW when 50 percent of the COVID effect is assumed. The COVID effects are estimated and applied at the rate by NEM status level.

Figure 6.6: COVID-19 Transition Path Assumption



7. EVTOU *Ex-Ante* Load Impact Study Findings

This section presents the *ex-ante* TOU load impacts for both electric vehicle rates, EVTOU2 and EVTOU5. *Ex-ante* TOU load impacts are not provided for the customers who switch from EVTOU2 to EVTOU5 or for customers in the VGI pilot.

7.1 Ex-Ante TOU load impacts for EVTOU2 customers

This subsection summarizes the *ex-ante* TOU peak load impact forecasts for customers anticipated to be enrolled in the EVTOU2 residential rate. Figure 7.1 shows aggregate loads and load impacts for EVTOU2 customers, in 2022 for an August SDG&E 1-in-2 average weekday. The average peak load impact is 11 percent of the reference load.

Figure 7.1: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU2 Customers,* (*August 2022 SDG&E 1-in-2 Average Weekday*)

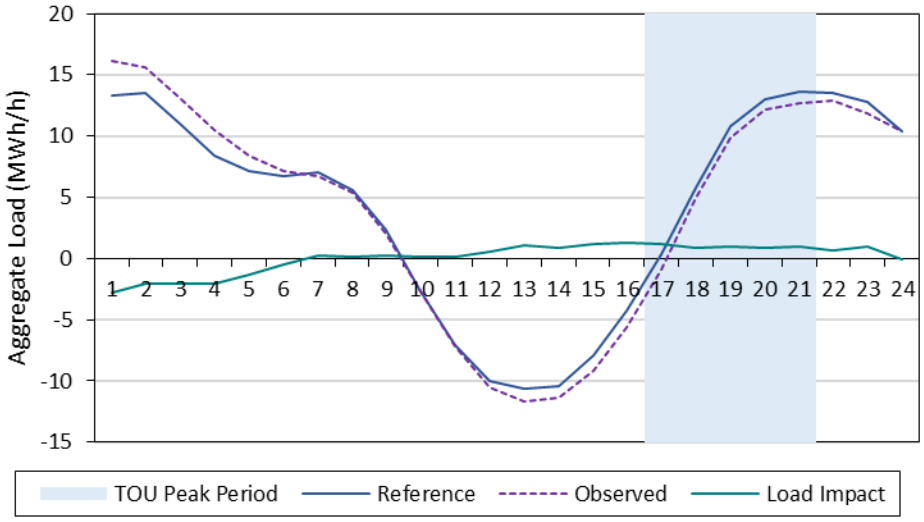


Figure 7.2 shows the monthly distributions of the peak-period TOU load impacts (TOU peak period aligns with the RA window) for EVTOU2 customers in 2022. Load impacts are greatest in the summer months June through October. Higher peak load impacts are expected to occur during the summer months based on the higher peak-hour prices relative to the standard non-TOU rate prices within the summer rate schedule. Results for the winter months are smaller – the two spring months, March and April, have positive load impacts while the remaining winter months yield negative load impacts.[38]

[38] The 2022 forecast assumes a zero percent COVID effect. The negative load impacts in some of the winter months stems from a *de-minimus* negative peak period load impact estimated for NEM customers in PY2019. (Differences between PY2019 and PY2020 NEM load impacts are assumed to be due to COVID. Thus, as the COVID effect is reduced to zero, NEM load impacts align with the PY2019 results.)

Figure 7.2: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU2 Customers,* (*2022 SDG&E 1-in-2 Average Weekday,* RA Window)

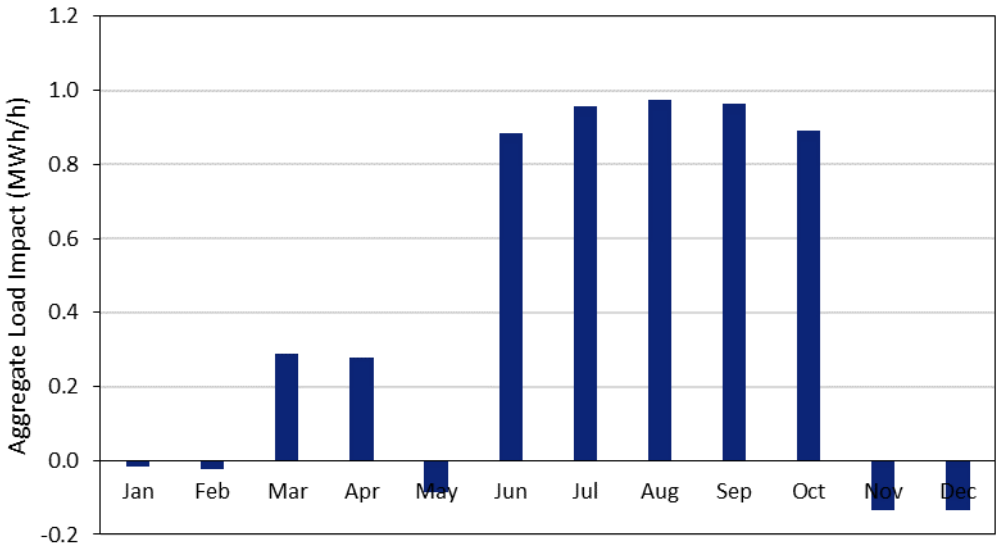
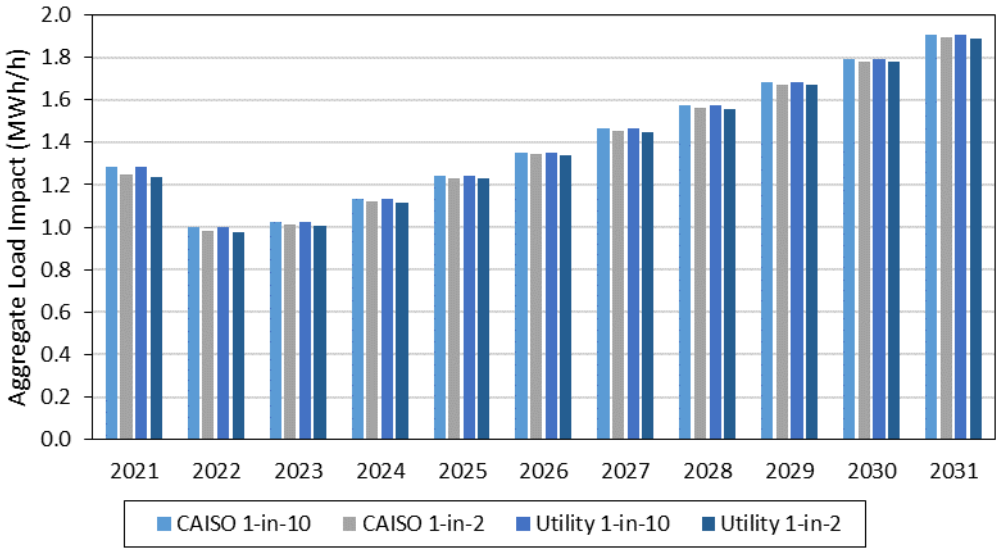


Figure 7.3 displays the aggregate average August weekday TOU load impacts over the forecast period, differentiated by weather scenario. The aggregate load impacts decrease in 2022 and increase thereafter because of the enrollment forecast. The load impacts are largest for the CAISO and Utility 1-in-10 scenarios, which have equivalent temperatures for the average August weekday. (TOU load impacts are largest for the Utility 1-in-10 scenarios on monthly peak days.)

Figure 7.3: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)



7.2 Ex-Ante TOU load impacts for EVTOU5 customers

This subsection summarizes the *ex-ante* TOU peak load impact forecasts for customers anticipated to be enrolled in the EVTOU5 rate. Figure 7.4 shows aggregate loads and load impacts for EVTOU5 customers, in 2022 for an August SDG&E 1-in-2 average weekday. The average peak load impact is 19 percent of the reference load.

Figure 7.4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU5 Customers,* (*August 2022 SDG&E 1-in-2 Average Weekday*)

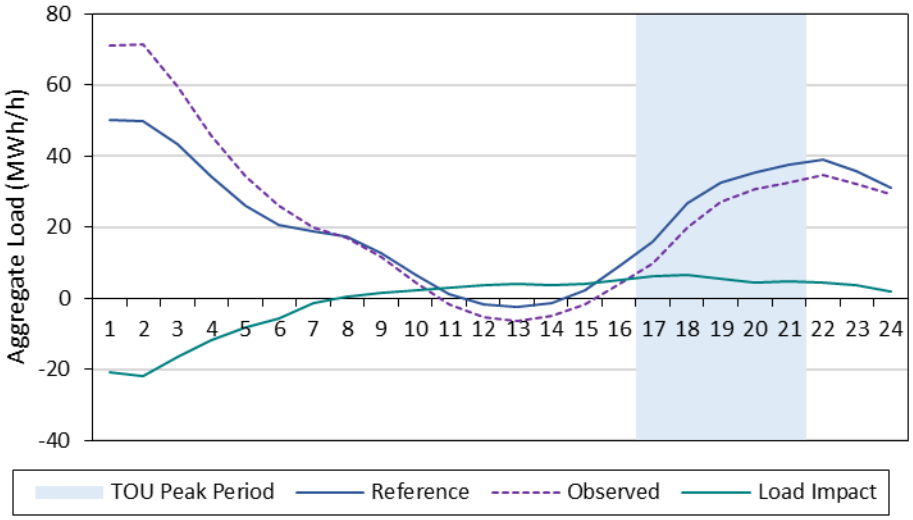


Figure 7.5 shows the monthly distributions of the peak-period TOU load impacts (TOU peak period aligns with the RA window) for EVTOU5 customers. Load impacts are greatest in December and November, even though peak period rates are higher in the summer than in winter months. The Spring months, March and April, exhibit the lowest peak period load impacts.

Figure 7.5: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU5 Customers,* (*2022 SDG&E 1-in-2 Average Weekday,* RA Window)

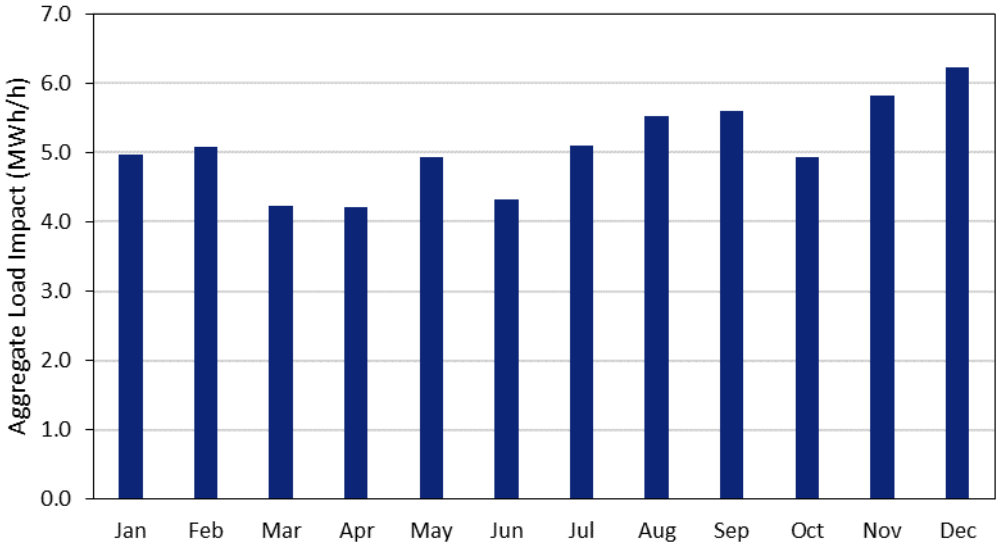
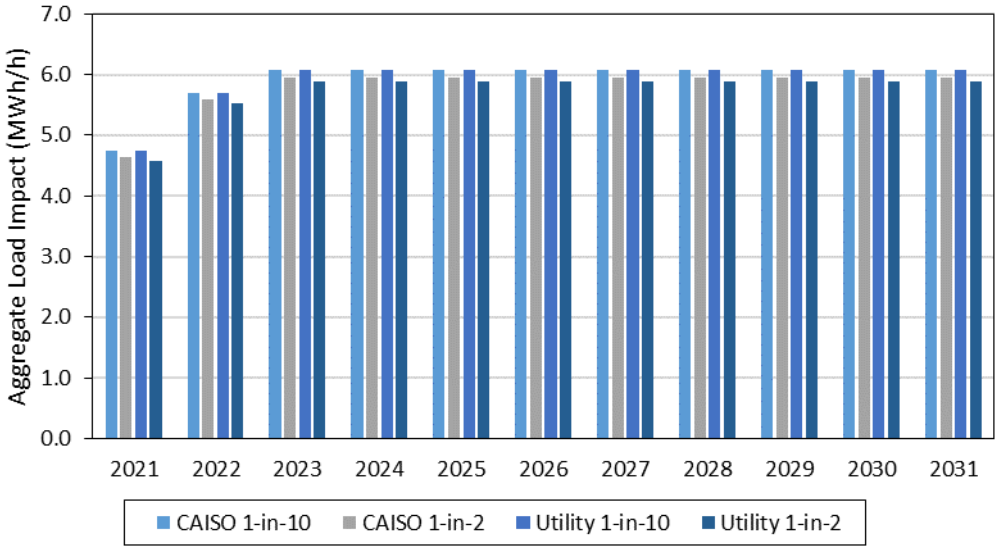


Figure 7.6 shows the aggregate average August weekday TOU load impacts over the forecast period, differentiated by weather scenario. The load impacts are largest for the CAISO and Utility 1-in-10 scenarios, which have equivalent temperatures for the average August weekday. (TOU load impacts are largest for the Utility 1-in-10 scenarios on monthly peak days.) Enrollment in EVTOU5 is expected to increase until 2023 and then remain constant, resulting in the aggregate load impact changes between years.

Figure 7.6: Aggregate TOU Load Impacts (MWh/h) – *EVTOU5* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)



8. Comparisons of Results

This section presents comparisons of current *ex-post* and *ex-ante* load impacts for SDG&E's EVTOU2 and EVTOU5 customers.

8.1 EVTOU2

8.1.1 Previous versus current *ex-post*

Table 8.1 shows the average EVTOU2 customer reference loads and load impacts for the August and January weekdays during the current and previous program years. Results are averaged over the RA window, which corresponds to the TOU peak period. Enrollment numbers have slightly decreased. The summer reference loads, however, increased in the current study as a result of higher usage during the COVID-19 pandemic. The per-customer load impact increased in the current study for the Summer period but decreased slightly during the Winter period.

Table 8.1: Comparison of Previous and Current *Ex-Post* EVTOU2 Load Impacts

Season	Result	*Ex-post 2019 Avg. Weekday Previous Study*	*Ex-post 2020 Avg. Weekday Current Study*
Summer (August)	# Enrolled	8,114	7,719
	Reference (MWh/h)	13.18	15.44
	Load Impact (MWh/h)	1.09	1.67
	Per-customer reference (kWh/h)	1.62	2.00
	Per-customer load impact (kWh/h)	0.13	0.22
	% Load Impact	8.2%	10.8%
	Temperature	74.7	77.8
Winter (January)	# Enrolled	8,927	7,403
	Reference (MWh/h)	14.09	10.97
	Load Impact (MWh/h)	0.93	0.50
	Per-customer reference (kWh/h)	1.58	1.48
	Per-customer load impact (kWh/h)	0.10	0.07
	% Load Impact	6.6%	4.6%
	Temperature	56.2	55.7

8.1.2 Previous versus current *ex-ante*

In this sub-section, the EVTOU2 *ex-ante* forecast prepared following PY2019 (the "previous study") are compared to the *ex-ante* forecast contained in this study (the "current study"). Table 8.2 reports the average RA-window load impacts for the August and January 2021 average weekday under utility-specific 1-in-2 weather conditions. The TOU RA window and peak-period remains the same in both forecasts. The current study forecasts a decrease in enrollment, which is associated with a decrease in aggregate

reference loads. Per-customer reference loads are similar during the Summer period; however, the current study load impacts are forecasted to be larger. Per-customer load impacts are smaller during the Winter period in the current study.

Table 8.2: Comparison of Previous and Current *Ex-Ante* EVTOU2 Load Impacts

Season	Result	*Ex-ante 2021 Avg. Weekday Previous Study*	*Ex-ante 2021 Avg. Weekday Current Study*
Summer (August)	# Enrolled	9,407	6,752
	Reference (MWh/h)	15.28	10.84
	Load Impact (MWh/h)	1.27	1.24
	Per-customer reference (kWh/h)	1.62	1.61
	Per-customer load impact (kWh/h)	0.13	0.18
	% Load Impact	8.3%	11.4%
	Temperature	76.3	76.8
Winter (January)	# Enrolled	9,429	7,178
	Reference (MWh/h)	14.48	11.89
	Load Impact (MWh/h)	0.72	0.44
	Per-customer reference (kWh/h)	1.54	1.66
	Per-customer load impact (kWh/h)	0.08	0.06
	% Load Impact	5.0%	3.7%
	Temperature	59.4	59.3

8.1.3 Previous *ex-ante* versus current *ex-post*

Table 8.3 provides a comparison of the *ex-ante* forecast of 2020 TOU load impacts prepared in the previous study and the PY2020 *ex-post* TOU load impacts estimated as part of this study for EVTOU2 customers. The *ex-ante* forecast shown in the table represents the August and January average weekday during a utility-specific 1-in-2 weather year. The *ex-post* load impacts are based on August and January weekdays. Enrollment decreased in the current *ex-post* study. The Summer aggregate reference load, however, increased due to higher energy consumption during the Covid-19 pandemic. The increased energy in 2020 provides more curtailable load during which is a possible reason for the larger per-customer load impacts. The *ex-post* Winter period was less affected by Covid-19 (since the pandemic began in March 2020). Therefore, the Winter per-customer reference loads and load impacts are similar between analyses.

Table 8.3: Comparison of Previous *Ex-Ante* and Current *Ex-Post* EVTOU2 Load Impacts

Season	Result	*Ex-ante 2020 Avg. Weekday Previous Study*	*Ex-post 2020 Avg. Weekday Current Study*
Summer (August)	# Enrolled	9,445	7,719
	Reference (MWh/h)	15.34	15.44
	Load Impact (MWh/h)	1.27	1.67
	Per-customer reference (kWh/h)	1.62	2.00
	Per-customer load impact (kWh/h)	0.13	0.22
	% Load Impact	8%	11%
	Temperature	76.3	77.8
Winter (January)	# Enrolled	9,467	7,403
	Reference (MWh/h)	14.54	10.97
	Load Impact (MWh/h)	0.73	0.50
	Per-customer reference (kWh/h)	1.54	1.48
	Per-customer load impact (kWh/h)	0.08	0.07
	% Load Impact	5.0%	4.6%
	Temperature	59.4	55.7

8.1.4 Current *ex-post* versus current *ex-ante*

Table 8.4 compares EVTOU2 customers' PY2020 *ex-post* TOU load impacts for the August and January average weekday with the corresponding *ex-ante* forecast for 2021 (of the SDG&E 1-in-2 August or January average weekday) produced in this study. The EVTOU2 customer TOU load impacts are presented for all EVTOU2 customers and are averaged over the RA window. Differences between *ex-post* and *ex-ante* load impacts stem from 1) changes in the number of customers and 2) Covid-19 adjusted reference loads and load impacts. The enrollments slightly decrease in the *ex-ante* analysis which leads to lower aggregate reference loads and load impacts. The effect of Covid is diminished in 2021, resulting in the *ex-ante* per-customer reference loads to be lower than *ex-post.* (Per-customer reference loads are lower in *ex-post* during the Winter period since the pandemic began in March 2020.) The load impact percent also differs slightly as the impact of Covid is reduced.[39]

[39] The *ex-ante* load impacts are calculated from the *ex-post* load impact percentages for non-NEM customers. The non-NEM load impact is therefore affected by Covid as reference loads have Covid adjustments. The load impacts for NEM customers tie back to the *ex-post* estimates from the PY2019 study as the effect of Covid diminishes.

Table 8.4: Comparison of Current *Ex-Post* and *Ex-Ante* EVTOU2 Load Impacts

Season	Result	*Ex-post 2020 Avg. Weekday Current Study*	*Ex-ante 2021 Avg. Weekday Current Study*
Summer (August)	# Enrolled	7,719	6,752
	Reference (MWh/h)	15.44	10.84
	Load Impact (MWh/h)	1.67	1.24
	Per-customer reference (kWh/h)	2.00	1.61
	Per-customer load impact (kWh/h)	0.22	0.18
	% Load Impact	10.8%	11.4%
	Temperature	77.8	76.8
Winter (January)	# Enrolled	7,403	7,178
	Reference (MWh/h)	10.97	11.89
	Load Impact (MWh/h)	0.50	0.44
	Per-customer reference (kWh/h)	1.48	1.66
	Per-customer load impact (kWh/h)	0.07	0.06
	% Load Impact	4.6%	3.7%
	Temperature	55.7	59.3

8.2 EVTOU5

8.2.1 Previous versus current *ex-post*

Table 8.5 shows the average EVTOU5 reference loads and load impacts for the average August and January weekday day during the current and previous program years, averaged over the RA window, which corresponds to the TOU peak period. Enrollment numbers have increased resulting in higher aggregate reference loads. The per-customer loads during the Summer period are higher as a result of Covid-19. The level and percentage load impacts are smaller in the current study.

Table 8.5: Comparison of Previous and Current *Ex-Post* EVTOU5 Load Impacts

Season	Result	*Ex-post 2019 Avg. Weekday Previous Study*	*Ex-post 2020 Avg. Weekday Current Study*
Summer (August)	# Enrolled	7,229	10,867
	Reference (MWh/h)	11.29	21.02
	Load Impact (MWh/h)	2.67	3.56
	Per-customer reference (kWh/h)	1.56	1.93
	Per-customer load impact (kWh/h)	0.37	0.33
	% Load Impact	23.6%	16.9%
	Temperature	75.2	78.1
Winter (January)	# Enrolled	3,219	8,763
	Reference (MWh/h)	5.24	12.89
	Load Impact (MWh/h)	1.22	2.42
	Per-customer reference (kWh/h)	1.63	1.47
	Per-customer load impact (kWh/h)	0.38	0.28
	% Load Impact	23.3%	18.8%
	Temperature	56.1	55.5

8.2.2 Previous versus current *ex-ante*

In this sub-section, the EVTOU5 *ex-ante* forecast prepared following PY2019 (the "previous study") are compared to the *ex-ante* forecast contained in this study (the "current study"). Table 8.6 reports the average RA-window load impacts for the August and January 2021 average weekday under utility-specific 1-in-2 weather conditions. The TOU RA window and peak-period remains the same in both forecasts. The current study forecasts an increase in enrollment (*e.g.,* 9,988 to 14,468 customers), which is associated with an increase in aggregate reference loads. Per-customer reference loads are higher in the current study because the effect of Covid-19 diminishes until there is zero effect in 2022. Per-customer load impact forecasts are smaller in the current study for both periods.

Table 8.6: Comparison of Previous and Current *Ex-Ante* EVTOU5 Load Impacts

Season	Result	*Ex-ante 2021 Avg. Weekday Previous Study*	*Ex-ante 2021 Avg. Weekday Current Study*
Summer (August)	# Enrolled	9,988	14,468
	Reference (MWh/h)	16.48	24.85
	Load Impact (MWh/h)	4.03	4.58
	Per-customer reference (kWh/h)	1.65	1.72
	Per-customer load impact (kWh/h)	0.40	0.32
	% Load Impact	24.4%	18.4%
	Temperature	76.6	76.9
Winter (January)	# Enrolled	9,173	12,379
	Reference (MWh/h)	15.65	23.02
	Load Impact (MWh/h)	3.64	3.61
	Per-customer reference (kWh/h)	1.71	1.86
	Per-customer load impact (kWh/h)	0.40	0.29
	% Load Impact	23.3%	15.7%
	Temperature	59.4	59.3

8.2.3 Previous *ex-ante* versus current *ex-post*

Table 8.7 provides a comparison of the *ex-ante* forecast of 2020 TOU load impacts prepared in the previous study and the PY2020 *ex-post* TOU load impacts estimated as part of this study for EVTOU5 customers. The *ex-ante* forecast shown in the table represents the August and January average weekday during a utility-specific 1-in-2 weather year. The *ex-post* load impacts are based on August and January weekdays. Increased enrollments lead to larger aggregate reference loads in the summer period. The per-customer winter reference loads are lower in the current *ex-post* analysis, resulting in lower aggregate reference loads. Per-customer load impacts were lower than forecasted in both periods.

Table 8.7: Comparison of Previous *Ex-Ante* and Current *Ex-Post* EVTOU5 Load Impacts

Season	Result	*Ex-ante* 2020 Avg. Weekday Previous Study	*Ex-post* 2020 Avg. Weekday Current Study
Summer (August)	# Enrolled	8,591	10,867
	Reference (MWh/h)	14.34	21.02
	Load Impact (MWh/h)	3.45	3.56
	Per-customer reference (kWh/h)	1.67	1.93
	Per-customer load impact (kWh/h)	0.40	0.33
	% Load Impact	24%	17%
	Temperature	76.6	78.1
Winter (January)	# Enrolled	7,777	8,763
	Reference (MWh/h)	12.95	12.89
	Load Impact (MWh/h)	2.96	2.42
	Per-customer reference (kWh/h)	1.67	1.47
	Per-customer load impact (kWh/h)	0.38	0.28
	% Load Impact	22.9%	18.8%
	Temperature	59.4	55.5

8.2.4 Current *ex-post* versus current *ex-ante*

Table 8.8 compares EVTOU5 customers' PY2020 *ex-post* TOU load impacts for the August and January average weekday with the corresponding *ex-ante* forecast for 2021 (of the SDG&E 1-in-2 August or January average weekday) produced in this study. The EVTOU5 customer TOU load impacts are presented for all EVTOU5 customers and are averaged over the RA window. Differences between *ex-post* and *ex-ante* load impacts stem from 1) changes in the number of customers and 2) Covid-19 adjusted reference loads and load impacts. Enrollments are forecasted to grow between 2021 and 2023, which leads to higher aggregate reference loads and load impacts. The effect of Covid is diminished in 2021, resulting in the *ex-ante* per-customer reference loads to be lower than *ex-post.* (Per-customer reference loads are lower in *ex-post* during the Winter period since the pandemic began in March 2020.) The load impact percent also differs slightly as the impact of Covid is reduced.[40]

[40] The *ex-ante* load impacts are calculated from the *ex-post* load impact percentages for non-NEM customers. The non-NEM load impact is therefore affected by Covid as reference loads have Covid adjustments. The load impacts for NEM customers tie back to the *ex-post* estimates from the PY2019 study as the effect of Covid diminishes.

Table 8.8: Comparison of Current *Ex-Post* and *Ex-Ante* EVTOU5 Load Impacts

Season	Result	*Ex-post 2020 Avg. Weekday Current Study*	*Ex-ante 2021 Avg. Weekday Current Study*
Summer (August)	# Enrolled	10,867	14,468
	Reference (MWh/h)	21.02	24.85
	Load Impact (MWh/h)	3.56	4.58
	Per-customer reference (kWh/h)	1.93	1.72
	Per-customer load impact (kWh/h)	0.33	0.32
	% Load Impact	17%	18%
	Temperature	78.1	76.9
Winter (January)	# Enrolled	8,763	12,379
	Reference (MWh/h)	12.89	23.02
	Load Impact (MWh/h)	2.42	3.61
	Per-customer reference (kWh/h)	1.47	1.86
	Per-customer load impact (kWh/h)	0.28	0.29
	% Load Impact	18.8%	15.7%
	Temperature	55.5	59.3

9. Recommendations

The ability to reliably estimate TOU load impacts for EV customers depends on knowing when the customer acquired and began charging the EV. In the absence of this information, the analysis runs the risk of confounding TOU price response with load changes due to EV adoption. While we believe we have developed a method that effectively identifies customers who have had an EV during our entire analysis period (before and after switching to an EVTOU rate), it would be helpful for SDG&E to consider whether it is feasible to collect additional information on customer EV adoption dates.

If looking to scale up VGI, the timing of the load impacts suggests a higher reliability value for the application of home charging than workplace, as more of the load impact occurs during the RA window. For workplace RTH, charging algorithms could be explored that alternate the charge pattern depending on current prices.

Appendices

The following Appendices are Excel files that can produce the tables required by the Protocols.

Appendix A: Residential Electric Vehicle TOU *Ex-Post* Load Impact Tables

Appendix B: Residential Electric Vehicle TOU *Ex-Ante* Load Impact Tables

Appendix C: EVTOU Customer Structural Breaks

The section provides additional details regarding the results of identifying structural breaks for incremental customers that adopted either the EVTOU2 or EVTOU5 rate. Recall that for each customer, CA Energy Consulting used weekly load data to estimate a structural break date in an attempt to identify whether a customer adopts an electric vehicle at some point within the analysis period. Customers that have a statistically significant structural break are assumed to have adopted an electric vehicle and are therefore removed from the analysis. The remaining customers (*i.e.,* those without statistically significant structural breaks in usage) are assumed to have an electric vehicle for the entire analysis period. Figure C.1 illustrates an example of a customer's average weekly usage per hour. The orange vertical line represents the date the customer joins an EVTOU rate, while the red vertical line represents the date of a structural break in usage (estimated from the statistical model). In this example, the structural break is statistically significant. Indeed, there is a noticeable difference in usage before and after the estimated structural break date.

Figure C.1: Structural Break Example

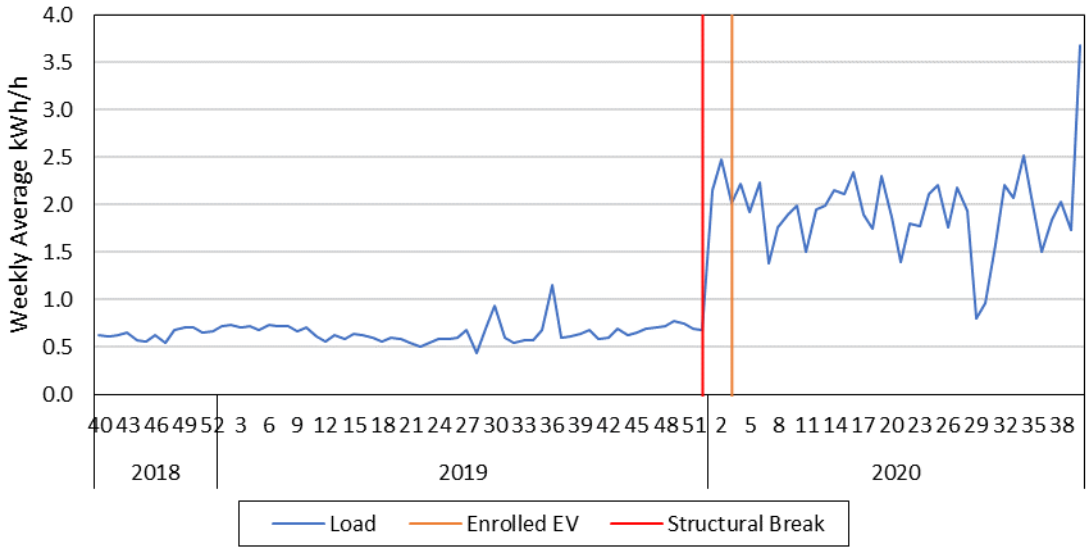


Table C.1 provides the resulting counts of EVTOU customers from the structural break tests. The "Removed" category represents the number of customers that were not included in the incremental EVTOU analysis because the structural break model indicated a statistically significant structural break. These customers are assumed to have adopted an EV during the analysis period and would therefore confound any EVTOU estimates if included. The "Included" customers represent those that did not have a statistically significant structural break and were consequently included in the analysis. Many customers were removed from the analysis, which is suggestive that many customers that adopt an electric vehicle switch to an EVTOU rate thereafter. A total of 79 out of 393 EVTOU2 and 337 out of 2,561 EVTOU5 customers were included in the analysis.

Table C.1: Count of Incremental EV Customers Based on Structural Breaks

NEM Status	Category	EVTOU2	EVTOU5
Non-NEM	Removed	225	1,870
	Included	47	234
	Total	**272**	**2104**
NEM	Removed	89	354
	Included	32	103
	Total	**121**	**457**

Ex-post load impacts were estimated separately using all incremental EVTOU customers as well as only those that did not have a statistically significant structural break. Comparing the load impacts of both cases helps illustrate the bias that is introduced from including customers that adopted an EV during the analysis period. Figure C.2 and Figure C.3 illustrates the *ex-post* EVTOU load impacts for EVTOU2 and EVTOU5 customers, respectively. The "All" line represents the load impacts when all enrolled customers are included in the analysis, whereas the "No Structural Break" line represents the load impacts when including only enrolled customers without a statistically significant structural break. For both EVTOU rates, the increase in usage during the morning hours for the "No Structural Break" customers is about half that of the version including all customers.

Figure C.2: *Ex-post* Load Impacts for Non-NEM Incremental EVTOU2 Customers

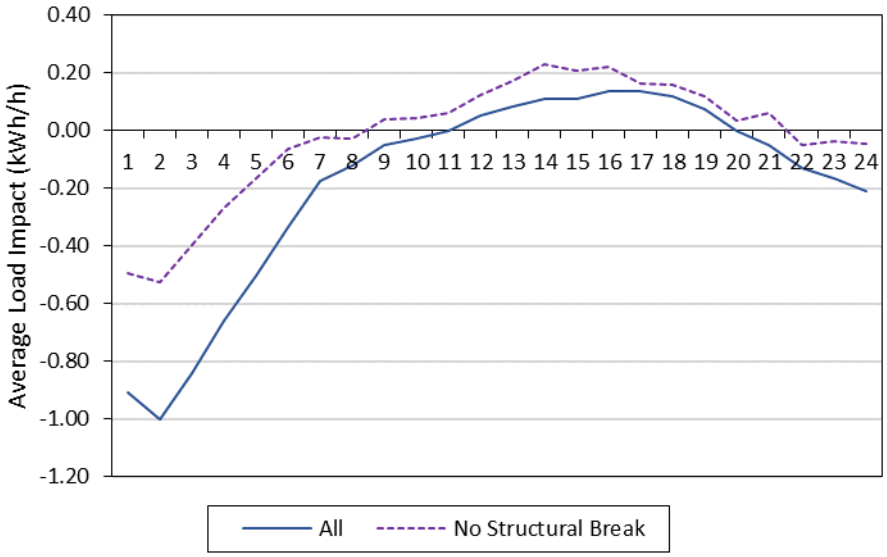
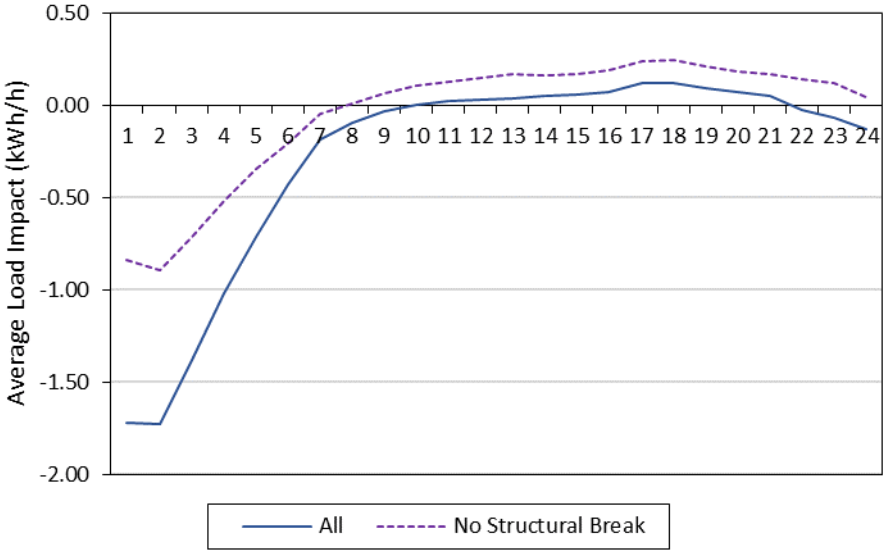



Figure C.3: *Ex-post* Load Impacts for Non-NEM Incremental EVTOU5 Customers