# 2019 Load Impact Evaluation of San Diego Gas and Electric's Electric Vehicle Rates

## CALMAC Study ID SDG0322

Michael Ty Clark
Nick Crowley
Daniel G. Hansen

*April 1, 2020*

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** ..... **0**
**Executive Summary** ..... **1**
ES.1 Resources Covered ..... 1
ES.2 Evaluation Methodologies ..... 1
ES.3 Ex-Post Load Impacts ..... 2
ES.3.1 TOU peak load impacts – EVTOU2 to EVTOU5 ..... 2
ES.3.2 TOU peak load impacts – Standard Tiered Rate to EVTOU2 ..... 3
ES.3.3 TOU peak load impacts – Standard Tiered Rate to EVTOU5 ..... 4
ES.4 Ex-Ante Load Impacts ..... 6
ES.4.1 Enrollment forecast ..... 6
ES.4.2 *Ex-Ante* load impacts – *Incremental* EVTOU2 ..... 7
ES.4.3 *Ex-Ante* load impacts – *Incremental* EVTOU2 ..... 8
**1. Introduction and Purpose of the Study** ..... **9**
**2. Description of Rates** ..... **9**
**3. *Ex-Post* Evaluation Methodology** ..... **11**
3.1 Data ..... 11
3.2 Analysis Methods ..... 11
3.2.1 Evaluation design and control group matching ..... 11
3.2.2 Fixed-effects panel regression models ..... 13
3.2.3 *Ex-post* models for estimating TOU load impacts ..... 13
3.2.4 Calculating uncertainty-adjusted load impacts ..... 15
3.2.5 Validity assessment ..... 15
3.3 Further Methods for EVTOU Analyses ..... 15
3.3.1 Transition from EVTOU2 to EVTOU5 Analysis ..... 16
3.3.2 Incremental EVTOU2 and EVTOU5 Analysis ..... 17
3.4 VGI Pilot Evaluation Methods ..... 19
**4. EVTOU *Ex-Post* Load Impact Study Findings** ..... **20**
4.1 TOU control group matching results for EVTOU2 to EVTOU5 customers ..... 21
4.2 Ex-post TOU load impacts for EVTOU2 to EVTOU5 customers ..... 22
4.3 Ex-post TOU load impacts for incremental EVTOU2 customers ..... 26
4.4 Ex-post TOU load impacts for incremental EVTOU5 customers ..... 29
**5. VGI Pilot Evaluation Study Findings** ..... **33**
**6. *Ex-Ante* Load Impacts** ..... **37**
6.1 Methodology ..... 38
6.1.1 Per-customer load impacts ..... 38
6.1.2 Per-customer reference loads ..... 38
6.1.3 Enrollment forecast ..... 39
6.2 Ex-Ante load impacts – Residential EVTOU2 ..... 40
6.3 Ex-Ante load impacts – Residential EVTOU5 ..... 42
**7. Comparisons of Results** ..... **44**
7.1 Current *ex-post* versus current *ex-ante* for EVTOU2 Customers ..... 44

7.2 Current *ex-post* versus current *ex-ante* for EVTOU5 Customers..... 45
**8. Recommendations .....46**
**Appendices.....47**
**Appendix C: EVTOU Customer Structural Breaks.....47**

**List of Tables**

Table ES.1: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Month* ..... 2
Table ES.2: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Season & Climate Zone* ..... 3
Table ES.3: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Month* ..... 4
Table ES.4: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Season & Climate Zone* ..... 4
Table ES.5 TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Month* ..... 5
Table ES.6: TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Season & Climate Zone* ..... 6
Table 3.1: Description of Variables Used in the TOU Analysis Regressions ..... 14
Table 3.2: Description of Variables Used in the Identification of Electric Vehicle Adoption Regressions ..... 18
Table 3.3 Description of Variables Used in the VGI Evaluation Regressions ..... 20
Table 4.1: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Month* ..... 23
Table 4.2: TOU Peak Load Impacts for EVTOU2 to EVTOU5 Customers – *Average Weekday by Season & Climate Zone* ..... 23
Table 4.3: TOU Average *Daily* Load Impacts for EVTOU2 to EVTOU5 Customers, *by Month* ..... 24
Table 4.4: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Month* ..... 27
Table 4.5: TOU Peak Load Impacts for EVTOU2 Customers – *Average Weekday by Season & Climate Zone* ..... 27
Table 4.6: TOU Average *Daily* Load Impacts for EVTOU2 Customers, *by Month* ..... 28
Table 4.7: TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Month* ..... 30
Table 4.8: TOU Peak Load Impacts for EVTOU5 Customers – *Average Weekday by Season & Climate Zone* ..... 31
Table 4.9: TOU Average *Daily* Load Impacts for EVTOU5 Customers, *by Month* ..... 31
Table 5.1 VGI Pilot Summary Statistics ..... 33
Table 5.2: VGI Regression Results ..... 37
Table 7.1: Comparison of Current *Ex-Post* and *Ex-Ante* TOU Load Impacts for EVTOU2 Customers ..... 45
Table 7.2: Comparison of Current *Ex-Post* and *Ex-Ante* TOU Load Impacts for EVTOU5 Customers ..... 46
Table C.1: Count of Incremental EV Customers Based on Structural Breaks ..... 48

**List of Figures**

Figure ES.1: Enrollments in EVTOU Rates ..... 7
Figure ES.2: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 7
Figure ES.3: Aggregate TOU Load Impacts (MWh/h) – *EVTOU5* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 8
Figure 2.1: EV Rate Time-of-Use Periods and Prices ..... 10
Figure 4.1: EVTOU2 to EVTOU5 and Matched Control Group Load Profiles – *Summer*... 21
Figure 4.2: EVTOU2 to EVTOU5 and Matched Control Group Load Profiles – *Winter*..... 22
Figure 4.3: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, August 2019*)..... 25
Figure 4.4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, January 2019*)..... 25
Figure 4.5: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 Customers (*Average Weekday, August 2019*) ..... 29
Figure 4.6: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 Customers (*Average Weekday, January 2019*)..... 29
Figure 4.7: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, August 2019*) ..... 32
Figure 4.8: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, January 2019*)..... 32
Figure 5.1: Distribution of VGI Pilot Charging Start Hours ..... 34
Figure 5.2: Distribution of Average VGI Pilot Session Prices ..... 34
Figure 5.3: Distribution of VGI Pilot Session Total Duration..... 35
Figure 5.4: VGI Pilot Session Box-Whisker Plots for Price, Charge, and Duration..... 36
Figure 6.1: Enrollments in EVTOU Rates..... 40
Figure 6.2: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU2 Customers,* (*August 2021 SDG&E 1-in-2 Average Weekday*)..... 40
Figure 6.3: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU2 Customers,* (*2021 SDG&E 1-in-2 Average Weekday,* RA Window) ..... 41
Figure 6.4: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 42
Figure 6.5: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU5 Customers,* (*August 2021 SDG&E 1-in-2 Average Weekday*)..... 42
Figure 6.6: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU5 Customers,* (*2021 SDG&E 1-in-2 Average Weekday,* RA Window) ..... 43
Figure 6.7: Aggregate TOU Load Impacts (MWh/h) – *EVTOU5* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)..... 44
Figure C.1: Structural Break Example ..... 47
Figure C.2: *Ex-post* Load Impacts for Non-NEM Incremental EVTOU2 Customers ..... 49
Figure C.3: *Ex-post* Load Impacts for Non-NEM Incremental EVTOU5 Customers ..... 49

# 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 516 in October 2018 to 2,341 in September 2019.[1] Peak load impacts appear similar across months, with small estimated load reductions in all months. The largest per-customer load reduction occurred in October, a decrease in usage of 0.14 kWh/h during the peak period. EVTOU2 customer enrollment declined over the study period from 9,228 to 8,039, while EVTOU5 customer enrollment increased from 1,584 to 7,618. Load impacts for customers on rate EVTOU2 were approximately the same across climate zones, but differed during the summer and winter periods, at 0.14 kWh/h and 0.08 kWh/h per customer, respectively. In contrast, load impacts for EVTOU5 customers were nearly the same across seasons, at 0.35 kWh/h per customer in the summer, and 0.34 kWh/h per customer in the winter.


[1] There were 1,219 incremental EVTOU2 to EVTOU5 customers with quality load data that were used in the regressions for estimating the EVTOU2 to EVTOU5 load impact.

# 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 EVTOU. 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 change 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 2018, and June through September 2019) and winter (November 2018 through May 2019) weekdays, by month. The count of customers that transitioned from EVTOU2 to EVTOU5 grew from 516 in October 2018 to 2,341 in September 2019.[2] Peak load impacts are similar across months, with small estimated load reductions in all months. The largest per-customer load reduction occurred in October, a decrease in usage of 0.14 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-18 | All | 516 | 0.79 | 0.07 | 1.52 | 0.14 | 68 |
| Nov-18 | All | 810 | 1.31 | 0.09 | 1.61 | 0.11 | 62 |
| Dec-18 | All | 895 | 1.64 | 0.09 | 1.83 | 0.10 | 56 |
| Jan-19 | All | 1,005 | 1.60 | 0.07 | 1.59 | 0.07 | 56 |
| Feb-19 | All | 2,353 | 3.70 | 0.13 | 1.57 | 0.05 | 52 |
| Mar-19 | All | 1,410 | 1.65 | 0.06 | 1.17 | 0.05 | 58 |
| Apr-19 | All | 1,598 | 1.63 | 0.11 | 1.02 | 0.07 | 63 |
| May-19 | All | 1,816 | 1.79 | 0.10 | 0.99 | 0.06 | 63 |
| Jun-19 | All | 1,967 | 2.11 | 0.15 | 1.07 | 0.08 | 68 |
| Jul-19 | All | 2,108 | 2.89 | 0.18 | 1.37 | 0.08 | 73 |
| Aug-19 | All | 2,255 | 3.46 | 0.15 | 1.53 | 0.06 | 75 |
| Sep-19 | All | 2,341 | 3.88 | 0.15 | 1.66 | 0.06 | 74 |

[2] There were 1,219 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. Although customers in both climate zones exhibit a small response, the inland climate per-customer load impact was approximately twice the per-customer load impact among coastal customers in both the summer and winter periods. However, due to differences in enrollment numbers, the aggregate impact of each climate zone is roughly the same.

**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 | 1,283 | 1.92 | 0.07 | 1.50 | 0.06 | 70 |
| | Inland | 554 | 0.70 | 0.06 | 1.26 | 0.12 | 77 |
| | **All** | **1,837** | **2.62** | **0.14** | **1.43** | **0.07** | **72** |
| Winter | Coastal | 992 | 1.42 | 0.05 | 1.43 | 0.05 | 59 |
| | Inland | 420 | 0.47 | 0.04 | 1.12 | 0.10 | 57 |
| | **All** | **1,412** | **1.89** | **0.10** | **1.34** | **0.07** | **58** |

## 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 fell throughout the period, with the numbers of enrolled customers falling from 9,228 in October 2018 to 8,039 in September 2019.[3] The decreasing enrollment is partially explained because of customers switching to the EVTOU5 rate. Differences in percentage load impacts across seasons is driven by load impacts of NEM customers.

[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 836 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-18 | All | 9,228 | 13.11 | 1.05 | 1.42 | 0.11 | 69 |
| Nov-18 | All | 8,993 | 13.62 | 0.91 | 1.52 | 0.10 | 63 |
| Dec-18 | All | 8,946 | 15.69 | 1.05 | 1.75 | 0.12 | 56 |
| Jan-19 | All | 8,927 | 14.09 | 0.93 | 1.58 | 0.10 | 56 |
| Feb-19 | All | 8,837 | 13.64 | 0.90 | 1.54 | 0.10 | 52 |
| Mar-19 | All | 8,685 | 10.16 | 0.34 | 1.17 | 0.04 | 58 |
| Apr-19 | All | 8,585 | 8.82 | 0.32 | 1.03 | 0.04 | 63 |
| May-19 | All | 8,469 | 8.69 | 0.65 | 1.03 | 0.08 | 63 |
| Jun-19 | All | 8,401 | 9.18 | 0.89 | 1.09 | 0.11 | 68 |
| Jul-19 | All | 8,258 | 11.63 | 1.03 | 1.41 | 0.12 | 73 |
| Aug-19 | All | 8,114 | 13.18 | 1.09 | 1.62 | 0.13 | 75 |
| Sep-19 | All | 8,039 | 13.51 | 1.07 | 1.68 | 0.13 | 74 |

Table ES.4 shows results by season and climate zone. The load impact estimates differ somewhat between climate zones. The inland load impact is 0.03 kWh/h higher than the coastal load impact, while average inland summer temperature is six degrees higher.

**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 | 5,980 | 8.97 | 0.78 | 1.50 | 0.13 | 70 |
| | Inland | 2,428 | 3.37 | 0.38 | 1.39 | 0.16 | 76 |
| | **All** | **8,408** | **12.34** | **1.16** | **1.47** | **0.14** | **72** |
| Winter | Coastal | 6,276 | 9.18 | 0.57 | 1.46 | 0.09 | 60 |
| | Inland | 2,502 | 3.07 | 0.17 | 1.23 | 0.07 | 57 |
| | **All** | **8,777** | **12.25** | **0.74** | **1.40** | **0.08** | **59** |

### 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 1,584 in October 2018 to 7,618 in September 2019.[4] The per-customer load impacts are relatively similar across seasons.[5]

**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-18 | All | 1,584 | 2.19 | 0.50 | 1.39 | 0.32 | 69 |
| Nov-18 | All | 2,196 | 3.51 | 0.81 | 1.60 | 0.37 | 62 |
| Dec-18 | All | 2,658 | 4.85 | 1.07 | 1.82 | 0.40 | 56 |
| Jan-19 | All | 3,219 | 5.24 | 1.22 | 1.63 | 0.38 | 56 |
| Feb-19 | All | 3,789 | 6.09 | 1.45 | 1.61 | 0.38 | 52 |
| Mar-19 | All | 4,459 | 5.28 | 1.25 | 1.18 | 0.28 | 58 |
| Apr-19 | All | 5,071 | 5.28 | 1.38 | 1.04 | 0.27 | 63 |
| May-19 | All | 5,741 | 6.18 | 1.94 | 1.08 | 0.34 | 63 |
| Jun-19 | All | 6,220 | 6.62 | 1.87 | 1.06 | 0.30 | 68 |
| Jul-19 | All | 6,732 | 9.16 | 2.34 | 1.36 | 0.35 | 74 |
| Aug-19 | All | 7,229 | 11.29 | 2.67 | 1.56 | 0.37 | 75 |
| Sep-19 | All | 7,618 | 12.64 | 2.83 | 1.66 | 0.37 | 74 |

Table ES.6 shows results by season and climate zone. The per customer reference load in the coastal climate zone is larger than in the inland climate zone. The coastal climate zone also has more than twice as many customers enrolled on EVTOU5. This results in an aggregate summer load impact of 1.55 MWh/h in the coastal climate zone versus only 0.57 MWh/h in the inland climate zone. The per-customer winter load impacts are similar between climate zones.

[4] 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 3,023 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.

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

**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 | 3,941 | 5.94 | 1.55 | 1.51 | 0.39 | 70 |
| | Inland | 1,935 | 2.55 | 0.57 | 1.32 | 0.29 | 77 |
| | **All** | **5,877** | **8.49** | **2.12** | **1.44** | **0.36** | **73** |
| Winter | Coastal | 2,634 | 3.67 | 0.89 | 1.39 | 0.34 | 60 |
| | Inland | 1,242 | 1.55 | 0.41 | 1.24 | 0.33 | 58 |
| | **All** | **3,876** | **5.22** | **1.30** | **1.35** | **0.34** | **59** |

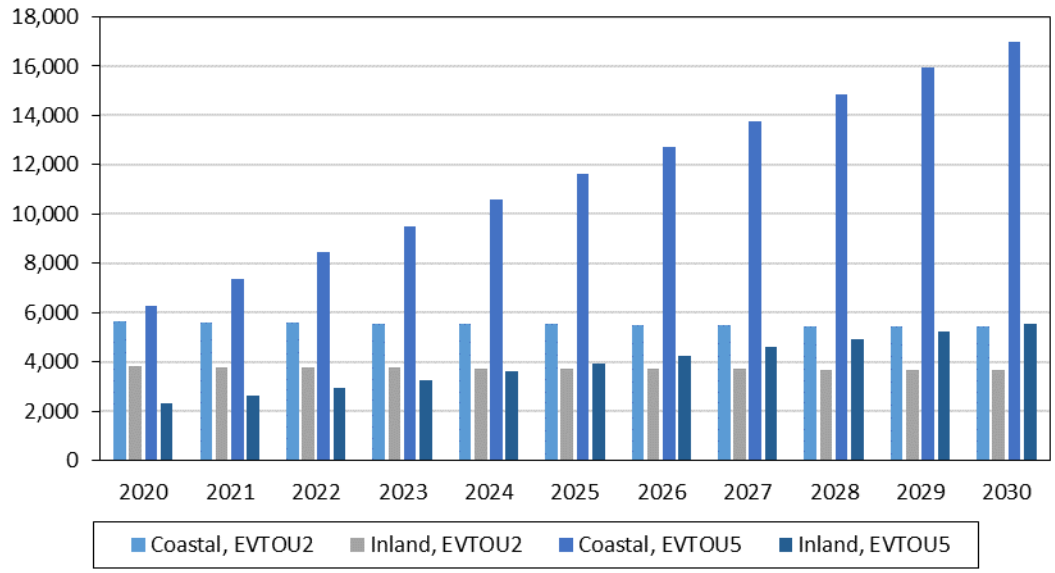
## *ES.4 Ex-Ante Load Impacts*

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 decline slightly over time for EVTOU2, while enrollment in EVTOU5 is forecasted to nearly triple among coastal customers by the end of the forecast period. EVTOU5 load impact enrollment is expected to be much greater in the Coastal climate zone than in the Inland.

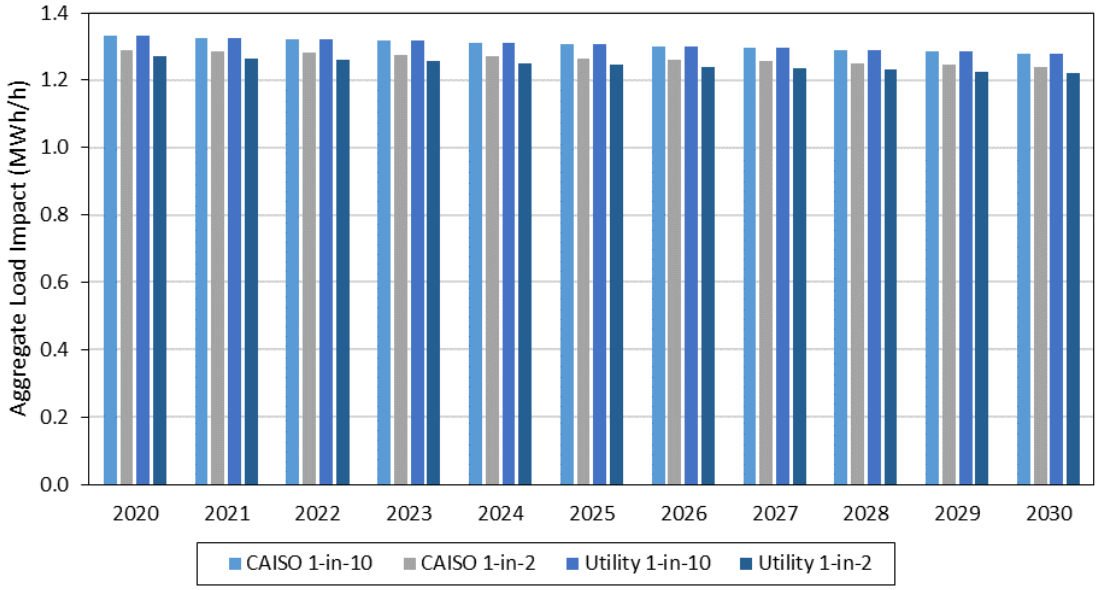
**Figure ES.1: Enrollments in EVTOU Rates**




## ES.4.2 *Ex-Ante* load impacts – *Incremental* 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.) The decrease of enrollment numbers over time drives aggregate impacts lower each year.

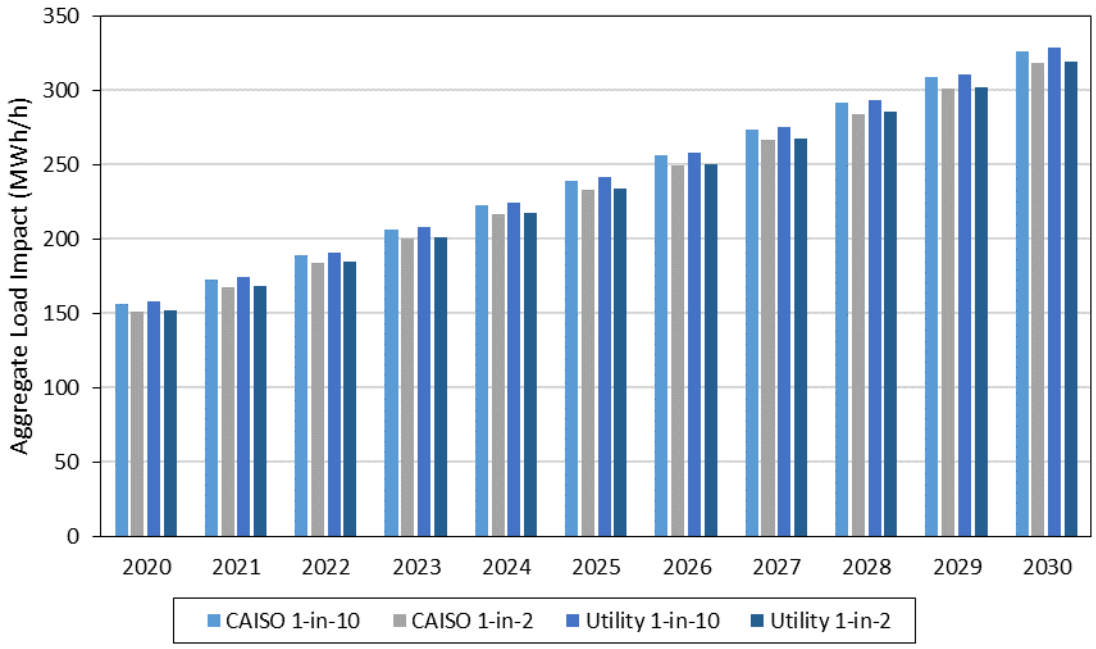
**Figure ES.2: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)**



### ES.4.3 *Ex-Ante* load impacts – *Incremental* EVTOU2

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.) Whereas enrollment in EVTOU2 is expected to decline over the next decade, enrollment in EVTOU5 is expected to climb, which drives the annual increases in aggregate load impact during the RA window.

**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, and 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.

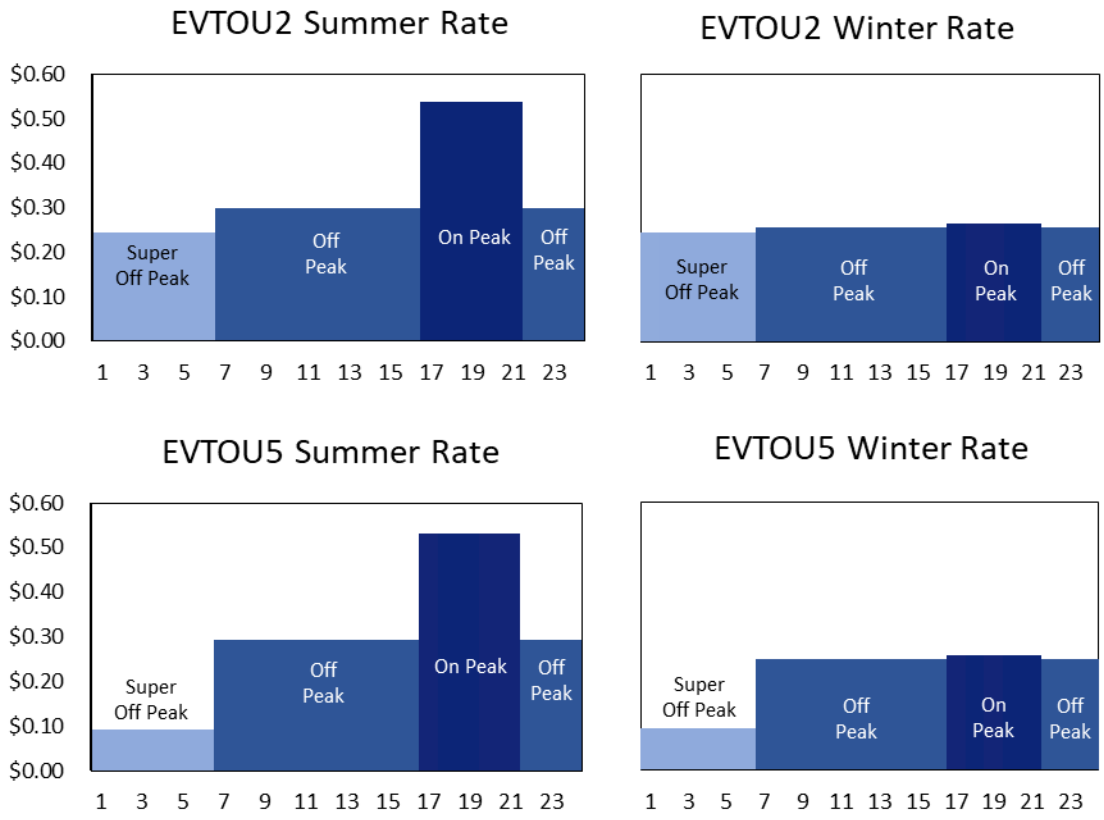
The report is organized as follows. Section 2 contains descriptions of the EVTOU2 and EVTOU5 rates; Section 3 describes the evaluation methods used in the study; Section 4 contains the TOU *ex-post* load impact results for EVTOU2 and EVTOU5 customers; Section 5 describes the VGI pilot evaluation findings; Section 6 describes the methods used to develop the *ex-ante* load impacts and the associated results; Section 7 provides a series of comparisons of *ex-post* and *ex-ante* results; and Section 8 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. The total rate is similar between EVTOU2 and EVTOU5 for all TOU periods except the super off-peak period, where the EVTOU5 rate $0.15 less than the EVTOU2 rate. 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.[6] 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.[7]

[6] 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.

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

# 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 2017 through September 2019;
- *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.

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 (October 2017 through September 2018). 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 analysis are separated by season, thus allowing different threshold dates that define incremental customers.[8] Specifically, incremental customers for the winter analysis are those that enrolled after June 1, 2018 while incremental customers for the summer analysis are those that enrolled after October 1, 2018. 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 2017 through May 2018, while the *summer* season used data for October 2017 and June through September of 2018.

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).[9] 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.[10] Second, NEM treatment customers must be matched to NEM control customers that have comparable solar photovoltaic generation

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

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

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

capacity sizes.[11] 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.[12]

### 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 TOU 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-holiday weekdays, a model is estimated that includes only days of that day type.[13] In this

[11] 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).

[12] 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.

[13] 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).

case, the model is simplified to include customer and date fixed effects, plus a variable to estimate the load impact (*i.e.*, the coefficient $\beta_1$). 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:[14]

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

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

**Table 3.1: Description of Variables Used in the TOU Analysis Regressions**

| Symbol | Description |
|---|---|
| $kWh_{c,d}$ | Load in a particular hour for customer *c* on date *d* |
| $TOU_c$ | Variable indicating whether customer *c* is a TOU (1) or Control (0) customer |
| $Evt_{c,d}$ | Variable indicating whether date *d* is an event day for customer *c* [15] |
| $Post_{c,d}$ | Variable indicating that date *d* is in the post-enrollment period for customer *c* |
| $AC_Evt_{c,d}$ | Variable indicating that date *d* is an *AC Saver Day Of* event day (1=event, 0 if not) for customer *c* |
| $\beta_0$ | Estimated constant coefficient |
| $\beta_1$ | Estimate of TOU load impact |
| $\beta_{2,Cust}$ and $\beta_{3,date}$ | Estimated customer and date fixed effects |
| $\beta_4$ | Estimate of average event-day load impact |
| $\beta_5$ and $\beta_6$ | Estimated average *TD* and SS event 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 |

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.,* $LI_{Daytype} = Ref_{Daytype}*PctLI_{Season}$).

[14] 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.

[15] For customers who are also enrolled to receive PTR-RYU alerts, that variable indicates that a day is a PTR-RYU event day.

### 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 $10^{th}$, $30^{th}$, $70^{th}$, and $90^{th}$ 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.

### 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, when they begin charging their electric vehicle at home.[16] 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.[17] Since we want to estimate the response to the EVTOU

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

[17] 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

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, 2018. This allows the use of October 1, 2017 through September 30, 2018 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 assumption that a customer enrolled on an EVTOU rate proxies 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.[18]

There were about 100 electric vehicle customers that were part of SDG&E's Smart Home Study which encouraged customers to enroll on the EVTOU5 rate. Any of these customers that transitioned to EVTOU5 were removed from the study to prevent confounding any results between the EVTOU2 to EVTOU5 analysis and the Smart Home Study.

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, 2017 through September 30, 2019) 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 effect regression model by different

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 affect with the TOU affect depending on when these changes occur and how close they are to each other.

[18] 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.

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, 2018. 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:

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

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 |
|---|---|
| $kWh_s$ | Average daily kWh during week *w* (weekends, holidays, and event days excluded) |
| $CDD60_w$ | Average cooling degree days[19] during week *w* |
| $HDD60_w$ | Average heating degree days[20] during week *w* |
| $Month_w$ | Monthly indicator variables |
| $\beta_0$ | Estimated constant coefficient |
| $\beta_1$ | Estimated effect of *CDD60* on daily kWh |
| $\beta_2$ | Estimated effect of *HDD60* on daily kWh |
| $\beta_{3,m}$ | Estimated effect of month *m* on daily kWh |
| $\varepsilon_w$ | 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.[21] 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. The same regression specifications are used as described above for estimated TOU load impacts. Separate TOU regressions are estimated by EVTOU rate, NEM, climate zone, and season.[22] 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. Therefore, the evaluation of incremental EVTOU customers implements a strictly before and after methodology.

[19] 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.

[20] 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.

[21] 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.

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

While this methodology does propose 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 affect usage by much. In which case, the model may not identify a structural break resulting in the customer being included in the analysis. Consequently, EVTOU load impacts would be overstated by demonstrating an increase in usage. 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; but in fact, they adopted an EV over the analysis period. The implication is 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 D 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:

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

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

**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 |
| $\beta_0$ | Estimated constant coefficient |
| $\beta_1$ | Estimated effect of price in session kWh charged |
| $\beta_2$ | Incremental estimated effect of price in session kWh charged for sessions billed to the driver |
| $\beta_3$ | Estimated effect of weather on the charge quantity |
| $\beta_{4,h}$ | Estimated effect of start hour *h* on the charge quantity |
| *Site* | Charging site fixed effects |
| *Driver* | Driver fixed effects |
| $\varepsilon_s$ | Error term |

The two coefficients of primary interest are $\beta_1$ and $\beta_2$. 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 $\beta_2$ 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.

While the VGI analyses do not readily conform to the Load Impact Protocols (*e.g.*, there aren't 1-in-2 and 1-in-10 schedules of hourly prices to align with the required scenarios), simulation-based results are provided that illustrate the magnitude of the estimated price effect.

# 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 5.2 percent, while the mean absolute percentage error (MAPE) is 5.3 percent. In the winter months, the MPE is 2.6 percent and the MAPE is 3.6 percent.

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

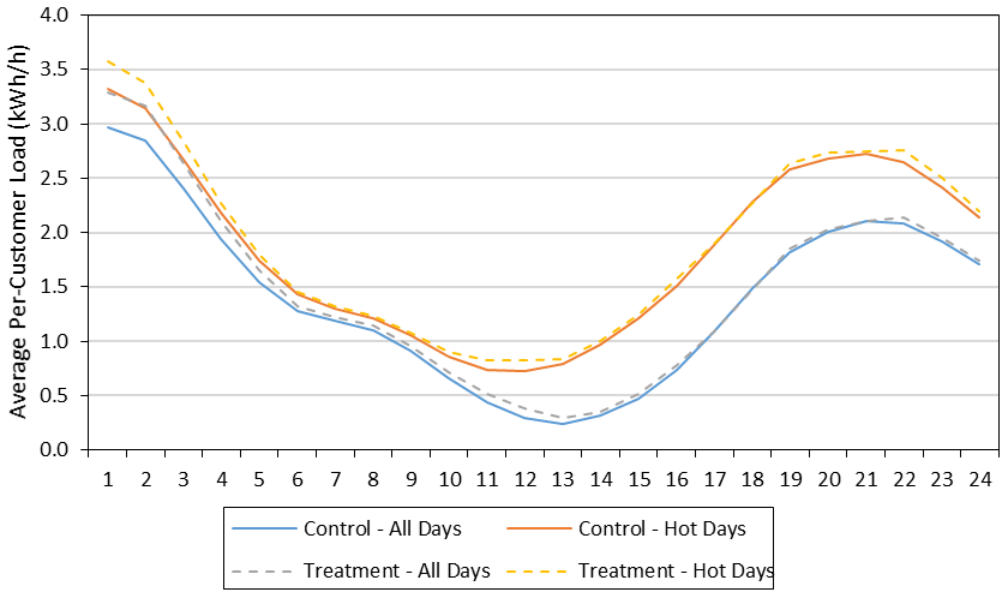
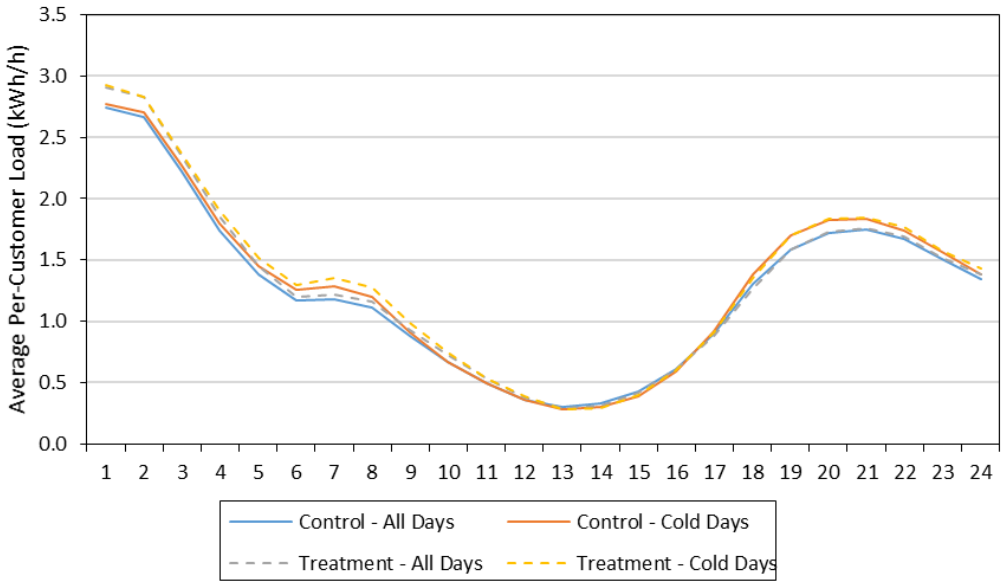


**Figure 4.2: EVTOU2 to EVTOU5 and Matched Control Group Load Profiles – *Winter***




## *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 2018, and June through September 2019) and winter (November 2018 through May 2019) weekdays, by month. The count of customers that transitioned from EVTOU2 to EVTOU5 grew from 516 in October 2018 to 2,341 in September 2019.[23] Peak load impacts are similar across months, with small estimated load reductions in all months. The largest per-customer load reduction occurred in October, a decrease in usage of 0.14 kWh/h during the peak period.

[23] There were 1,219 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-18 | All | 516 | 0.79 | 0.07 | 1.52 | 0.14 | 68 |
| Nov-18 | All | 810 | 1.31 | 0.09 | 1.61 | 0.11 | 62 |
| Dec-18 | All | 895 | 1.64 | 0.09 | 1.83 | 0.10 | 56 |
| Jan-19 | All | 1,005 | 1.60 | 0.07 | 1.59 | 0.07 | 56 |
| Feb-19 | All | 2,353 | 3.70 | 0.13 | 1.57 | 0.05 | 52 |
| Mar-19 | All | 1,410 | 1.65 | 0.06 | 1.17 | 0.05 | 58 |
| Apr-19 | All | 1,598 | 1.63 | 0.11 | 1.02 | 0.07 | 63 |
| May-19 | All | 1,816 | 1.79 | 0.10 | 0.99 | 0.06 | 63 |
| Jun-19 | All | 1,967 | 2.11 | 0.15 | 1.07 | 0.08 | 68 |
| Jul-19 | All | 2,108 | 2.89 | 0.18 | 1.37 | 0.08 | 73 |
| Aug-19 | All | 2,255 | 3.46 | 0.15 | 1.53 | 0.06 | 75 |
| Sep-19 | All | 2,341 | 3.88 | 0.15 | 1.66 | 0.06 | 74 |

Table 4.2 summarizes results by season and climate zone. Although customers in both climate zones exhibit a small response, the inland climate per-customer load impact was approximately twice the per-customer load impact among coastal customers in both the summer and winter periods. However, due to differences in enrollment numbers, the aggregate impact of each climate zone is roughly the same.

**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 | 1,283 | 1.92 | 0.07 | 1.50 | 0.06 | 70 |
| | Inland | 554 | 0.70 | 0.06 | 1.26 | 0.12 | 77 |
| | **All** | **1,837** | **2.62** | **0.14** | **1.43** | **0.07** | **72** |
| Winter | Coastal | 992 | 1.42 | 0.05 | 1.43 | 0.05 | 59 |
| | Inland | 420 | 0.47 | 0.04 | 1.12 | 0.10 | 57 |
| | **All** | **1,412** | **1.89** | **0.10** | **1.34** | **0.07** | **58** |

Table 4.3 shows the effect of TOU on average daily usage by month. Customers that transitioned to EVTOU5 *increased* overall usage during all months compared with their usage under EVTOU2, particularly during non-peak hours. The overall effect is an average annual *increase* of about 1.64 kWh/h per customer.

**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-18 | All | 516 | 16.7 | -0.3 | 32.3 | -0.5 | 64 |
| Nov-18 | All | 810 | 24.6 | -1.5 | 30.3 | -1.9 | 61 |
| Dec-18 | All | 895 | 30.6 | -1.3 | 34.2 | -1.4 | 55 |
| Jan-19 | All | 1,005 | 31.3 | -2.1 | 31.2 | -2.1 | 54 |
| Feb-19 | All | 2,353 | 72.3 | -4.5 | 30.7 | -1.9 | 50 |
| Mar-19 | All | 1,410 | 37.1 | -2.4 | 26.3 | -1.7 | 55 |
| Apr-19 | All | 1,598 | 38.3 | -1.7 | 24.0 | -1.1 | 60 |
| May-19 | All | 1,816 | 45.1 | -3.0 | 24.8 | -1.7 | 60 |
| Jun-19 | All | 1,967 | 53.8 | -2.0 | 27.4 | -1.0 | 65 |
| Jul-19 | All | 2,108 | 62.3 | -3.5 | 29.5 | -1.6 | 69 |
| Aug-19 | All | 2,255 | 71.5 | -4.5 | 31.7 | -2.0 | 70 |
| Sep-19 | All | 2,341 | 80.1 | -4.5 | 34.2 | -1.9 | 70 |

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 of off-peak hours. Nearly all of the increased usage occurs in the morning hours, which corresponds with when the EVTOU5 rate has a reduced rate of $0.15 relative to EVTOU2.

**Figure 4.3: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, August 2019*)**

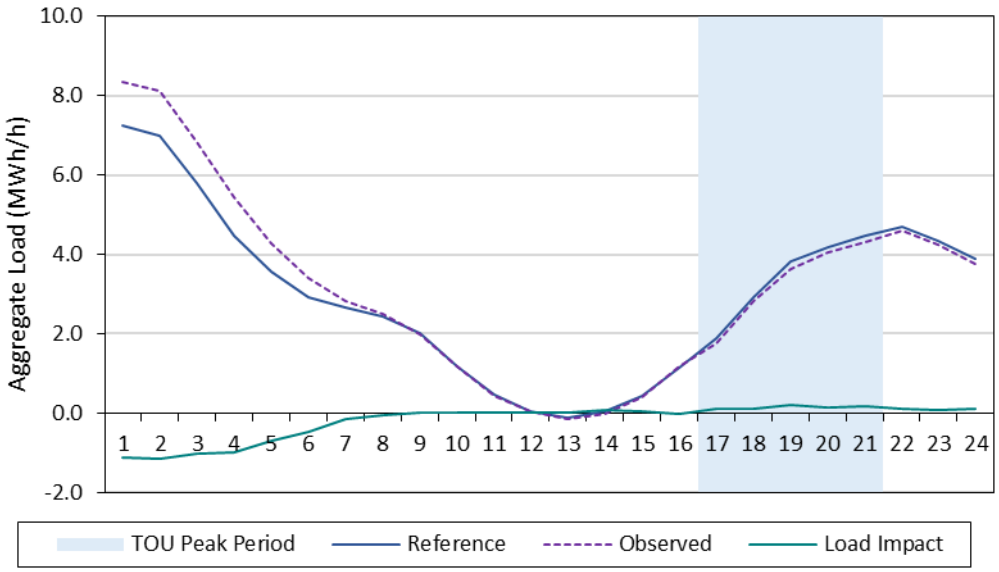
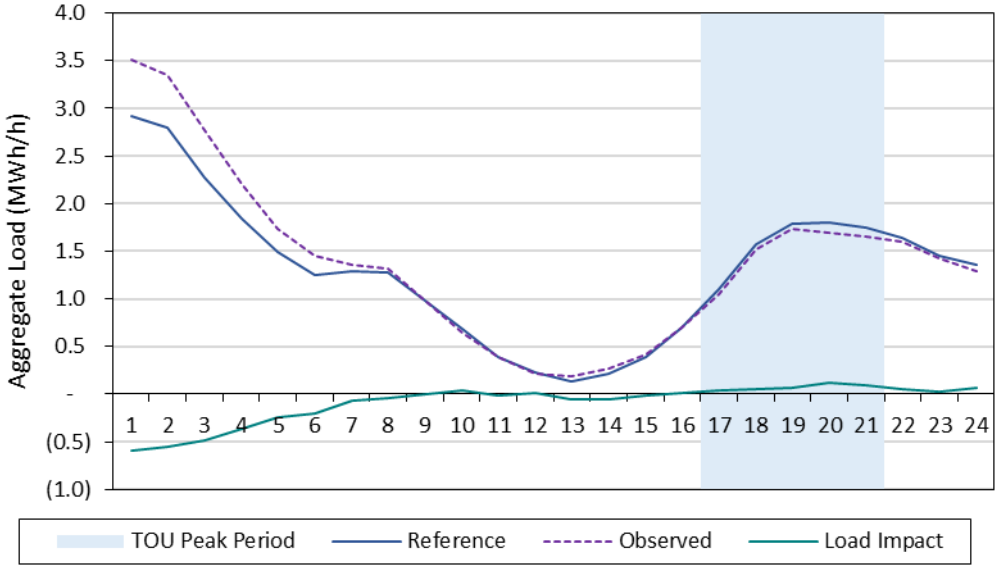



**Figure 4.4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 to EVTOU5 Customers (*Average Weekday, January 2019*)**



## *4.3 Ex-post TOU load impacts for incremental 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 2018). The winter months are indicated by light blue shading. Enrollment slightly fell throughout the period, with the numbers of enrolled customers falling from 9,228 in October 2018 to 8,039 in September 2019.[24] The decreasing enrollment is partially explained because of customers switching to the EVTOU5 rate. 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, the 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, followed by the winter period, and lowest for the March and April season. The largest per-customer load impact of 0.134 kWh/h occurs in August, which also has the highest average event-hour temperature.

[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 836 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 4.4: 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-18 | All | 9,228 | 13.11 | 1.05 | 1.42 | 0.11 | 69 |
| Nov-18 | All | 8,993 | 13.62 | 0.91 | 1.52 | 0.10 | 63 |
| Dec-18 | All | 8,946 | 15.69 | 1.05 | 1.75 | 0.12 | 56 |
| Jan-19 | All | 8,927 | 14.09 | 0.93 | 1.58 | 0.10 | 56 |
| Feb-19 | All | 8,837 | 13.64 | 0.90 | 1.54 | 0.10 | 52 |
| Mar-19 | All | 8,685 | 10.16 | 0.34 | 1.17 | 0.04 | 58 |
| Apr-19 | All | 8,585 | 8.82 | 0.32 | 1.03 | 0.04 | 63 |
| May-19 | All | 8,469 | 8.69 | 0.65 | 1.03 | 0.08 | 63 |
| Jun-19 | All | 8,401 | 9.18 | 0.89 | 1.09 | 0.11 | 68 |
| Jul-19 | All | 8,258 | 11.63 | 1.03 | 1.41 | 0.12 | 73 |
| Aug-19 | All | 8,114 | 13.18 | 1.09 | 1.62 | 0.13 | 75 |
| Sep-19 | All | 8,039 | 13.51 | 1.07 | 1.68 | 0.13 | 74 |

Table 4.5 shows results by season and climate zone. The load impacts differ somewhat between climate zones. The inland load impact is 0.03 kWh/h higher than the coastal load impact, while average inland summer temperature is six degrees higher.

**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 | 5,980 | 8.97 | 0.78 | 1.50 | 0.13 | 70 |
| | Inland | 2,428 | 3.37 | 0.38 | 1.39 | 0.16 | 76 |
| | **All** | **8,408** | **12.34** | **1.16** | **1.47** | **0.14** | **72** |
| Winter | Coastal | 6,276 | 9.18 | 0.57 | 1.46 | 0.09 | 60 |
| | Inland | 2,502 | 3.07 | 0.17 | 1.23 | 0.07 | 57 |
| | **All** | **8,777** | **12.25** | **0.74** | **1.40** | **0.08** | **59** |

Table 4.6 shows the effect of EVTOU2 on average *daily* usage by month. EVTOU2 customers increased their energy consumption in all months. As will be shown below, the increase in usage occurs during the morning hours.

**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-18 | All | 9,228 | 245.22 | -3.86 | 26.57 | -0.42 | 66 |
| Nov-18 | All | 8,993 | 238.71 | -1.99 | 26.54 | -0.22 | 61 |
| Dec-18 | All | 8,946 | 271.62 | -1.31 | 30.36 | -0.15 | 55 |
| Jan-19 | All | 8,927 | 251.83 | -2.11 | 28.21 | -0.24 | 54 |
| Feb-19 | All | 8,837 | 244.93 | -2.54 | 27.72 | -0.29 | 50 |
| Mar-19 | All | 8,685 | 197.80 | -7.51 | 22.78 | -0.86 | 55 |
| Apr-19 | All | 8,585 | 172.05 | -6.74 | 20.04 | -0.79 | 60 |
| May-19 | All | 8,469 | 177.61 | -2.85 | 20.97 | -0.34 | 60 |
| Jun-19 | All | 8,401 | 181.06 | -2.64 | 21.55 | -0.31 | 65 |
| Jul-19 | All | 8,258 | 202.63 | -1.58 | 24.54 | -0.19 | 69 |
| Aug-19 | All | 8,114 | 218.03 | -1.36 | 26.87 | -0.17 | 70 |
| Sep-19 | All | 8,039 | 225.20 | -1.50 | 28.01 | -0.19 | 70 |

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. There is a significant increase in usage during the super off-peak hours when the rate is lowest. This suggest 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 2019*)**

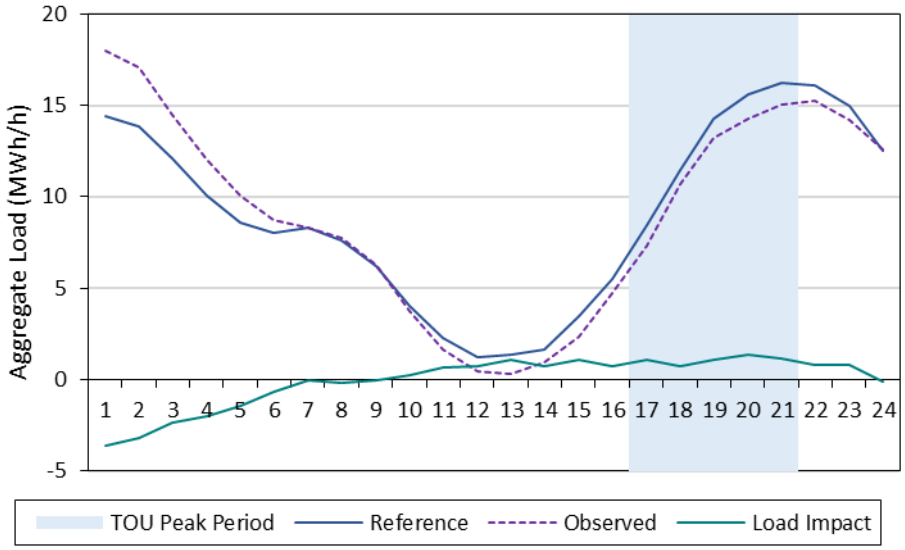
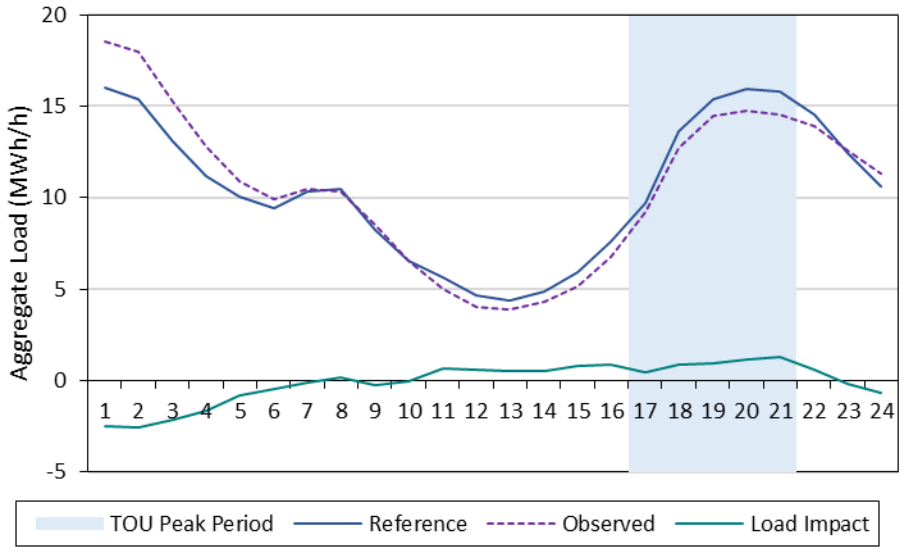



**Figure 4.6: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU2 Customers (*Average Weekday, January 2019*)**




## *4.4 Ex-post TOU load impacts for incremental 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 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 2018). The winter months are indicated by light blue shading. Enrollment additions continued throughout the period, with the numbers of enrolled customers rising from 1,584 in October 2018 to 7,618 in September 2019.[25] The per-customer load impacts are relatively similar across all seasons.[26] The largest per-customer load impact of 0.402 kWh/h occurs in December.

**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-18 | All | 1,584 | 2.19 | 0.50 | 1.39 | 0.32 | 69 |
| Nov-18 | All | 2,196 | 3.51 | 0.81 | 1.60 | 0.37 | 62 |
| Dec-18 | All | 2,658 | 4.85 | 1.07 | 1.82 | 0.40 | 56 |
| Jan-19 | All | 3,219 | 5.24 | 1.22 | 1.63 | 0.38 | 56 |
| Feb-19 | All | 3,789 | 6.09 | 1.45 | 1.61 | 0.38 | 52 |
| Mar-19 | All | 4,459 | 5.28 | 1.25 | 1.18 | 0.28 | 58 |
| Apr-19 | All | 5,071 | 5.28 | 1.38 | 1.04 | 0.27 | 63 |
| May-19 | All | 5,741 | 6.18 | 1.94 | 1.08 | 0.34 | 63 |
| Jun-19 | All | 6,220 | 6.62 | 1.87 | 1.06 | 0.30 | 68 |
| Jul-19 | All | 6,732 | 9.16 | 2.34 | 1.36 | 0.35 | 74 |
| Aug-19 | All | 7,229 | 11.29 | 2.67 | 1.56 | 0.37 | 75 |
| Sep-19 | All | 7,618 | 12.64 | 2.83 | 1.66 | 0.37 | 74 |

Table 4.8 shows results by season and climate zone. The per-customer reference load in the coastal climate zone is larger than in the inland climate zone. The coastal climate zone also has more than twice as many customers enrolled on EVTOU5. This results in an aggregate summer load impact of 1.55 MWh/h in the coastal climate zone versus only 0.57 MWh/h in the inland climate zone. The per-customer winter load impacts are similar between climate zones.

[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 3,023 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 TOU 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.

**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 | 3,941 | 5.94 | 1.55 | 1.51 | 0.39 | 70 |
| | Inland | 1,935 | 2.55 | 0.57 | 1.32 | 0.29 | 77 |
| | **All** | **5,877** | **8.49** | **2.12** | **1.44** | **0.36** | **73** |
| Winter | Coastal | 2,634 | 3.67 | 0.89 | 1.39 | 0.34 | 60 |
| | Inland | 1,242 | 1.55 | 0.41 | 1.24 | 0.33 | 58 |
| | **All** | **3,876** | **5.22** | **1.30** | **1.35** | **0.34** | **59** |

Table 4.9 shows the effect of EVTOU5 on average *daily* usage by month. EVTOU5 customers decreased their energy consumption during the summer months but increased consumption during the winter months. The overall change was an average annual *increase* of 3 percent.

**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-18 | All | 1,584 | 45.61 | 0.73 | 28.79 | 0.46 | 65 |
| Nov-18 | All | 2,196 | 60.97 | -2.06 | 27.77 | -0.94 | 61 |
| Dec-18 | All | 2,658 | 82.35 | -1.92 | 30.98 | -0.72 | 54 |
| Jan-19 | All | 3,219 | 91.86 | -3.16 | 28.54 | -0.98 | 54 |
| Feb-19 | All | 3,789 | 106.20 | -3.99 | 28.03 | -1.05 | 50 |
| Mar-19 | All | 4,459 | 104.75 | -3.84 | 23.49 | -0.86 | 55 |
| Apr-19 | All | 5,071 | 105.66 | -4.28 | 20.84 | -0.84 | 60 |
| May-19 | All | 5,741 | 124.57 | -7.23 | 21.70 | -1.26 | 60 |
| Jun-19 | All | 6,220 | 148.53 | 2.84 | 23.88 | 0.46 | 65 |
| Jul-19 | All | 6,732 | 179.24 | 5.73 | 26.62 | 0.85 | 69 |
| Aug-19 | All | 7,229 | 211.55 | 6.47 | 29.26 | 0.90 | 70 |
| Sep-19 | All | 7,618 | 236.29 | 6.73 | 31.02 | 0.88 | 70 |

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. Figure 4.8 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 7-16 and HE 22-24).

The greatest decrease in usage occurs during the peak period, and as seen among 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.

**Figure 4.7: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, August 2019*)**

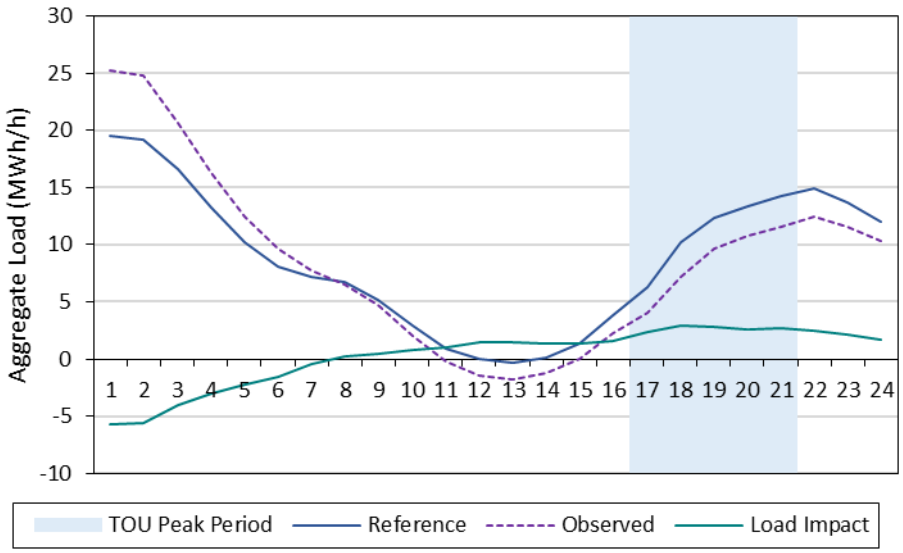
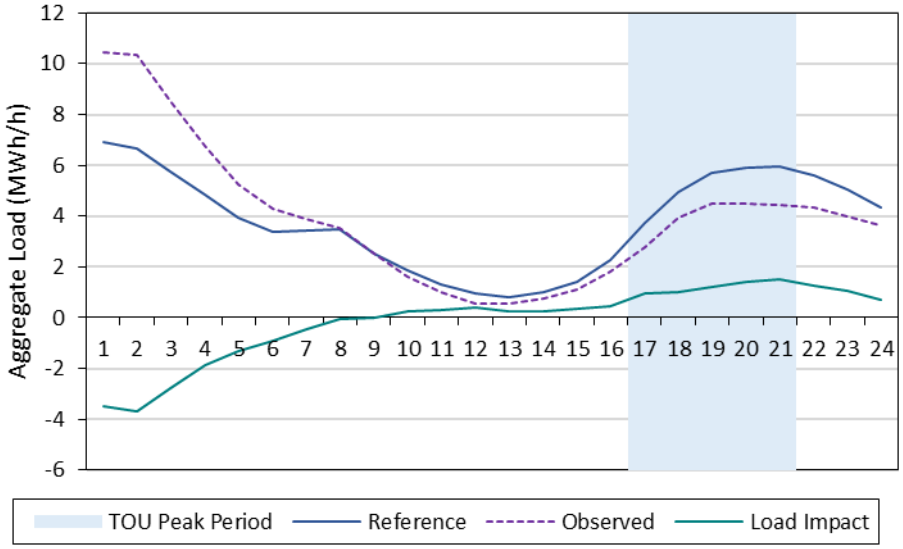



**Figure 4.8: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – EVTOU5 Customers (*Average Weekday, January 2019*)**



# 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 2017 through September 2019. 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.

**Table 5.1 VGI Pilot Summary Statistics**

| Characteristics | Work | | Home |
|---|---|---|---|
| | Rate to Host | Rate to Driver | Rate to Driver |
| Stations | 595 | 961 | 510 |
| EV Drivers | 30 | 966 | 319 |
| Sessions | 95,387 | 67,162 | 35,466 |
| Avg Start Time | 10:33 | 8:67 | 16:57 |
| | (5.91) | (3.68) | (6.66) |
| Avg Duration (hours) | 7.71 | 5.43 | 6.13 |
| | (6.26) | (3.70) | (5.38) |
| Avg kWh | 9.94 | 9.25 | 6.99 |
| | (10.09) | (8.48) | (9.35) |
| Avg Price | 0.26 | 0.20 | 0.20 |
| | (0.18) | (0.12) | (0.10) |

Note: Standard errors in parentheses.

Figure 5.1 illustrates the distribution of session charge start times by VGI facility/payment type. Vehicles that are plugged into the home facilities have over 30 percent of charge times starting at the end 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 5.1: Distribution of VGI Pilot Charging Start Hours**

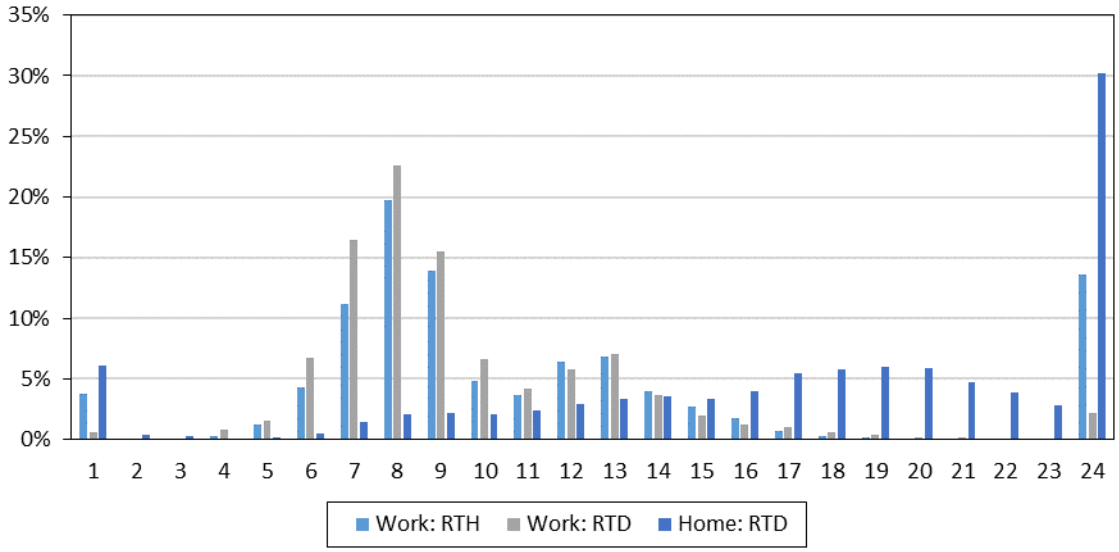



Figure 5.2 illustrates the distribution of the average price during VGI facility sessions.[27] Notice the comparatively high share of work / rate-to-host sessions at higher price levels, particularly at $0.70 per kWh. This may indicate that the plug-in decision for these customers is less sensitive to price than customers who pay the rate (either at work or at home).

**Figure 5.2: Distribution of Average VGI Pilot Session Prices**

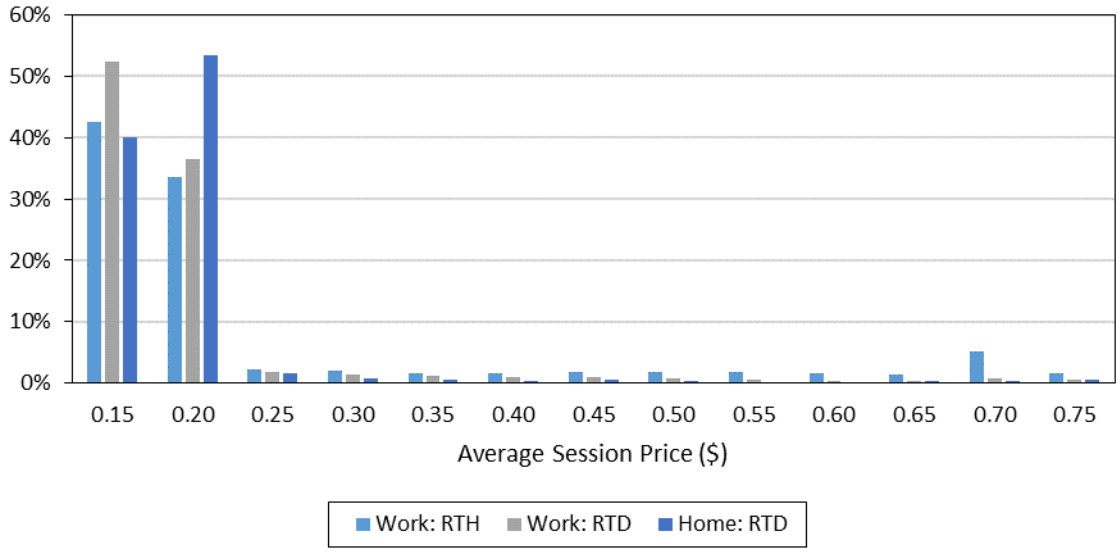



Figure 5.3 shows the frequency distribution of session duration, separated by charging location and who pays. It appears that work / rate-to-host sessions have the highest

[27] The figure is censored between $0.15 and $0.75, which represents 99 percent of all session prices.

share of short-duration sessions (two hours or less), while home charging sessions are most likely to last a full 24 hours.

**Figure 5.3: Distribution of VGI Pilot Session Total Duration**

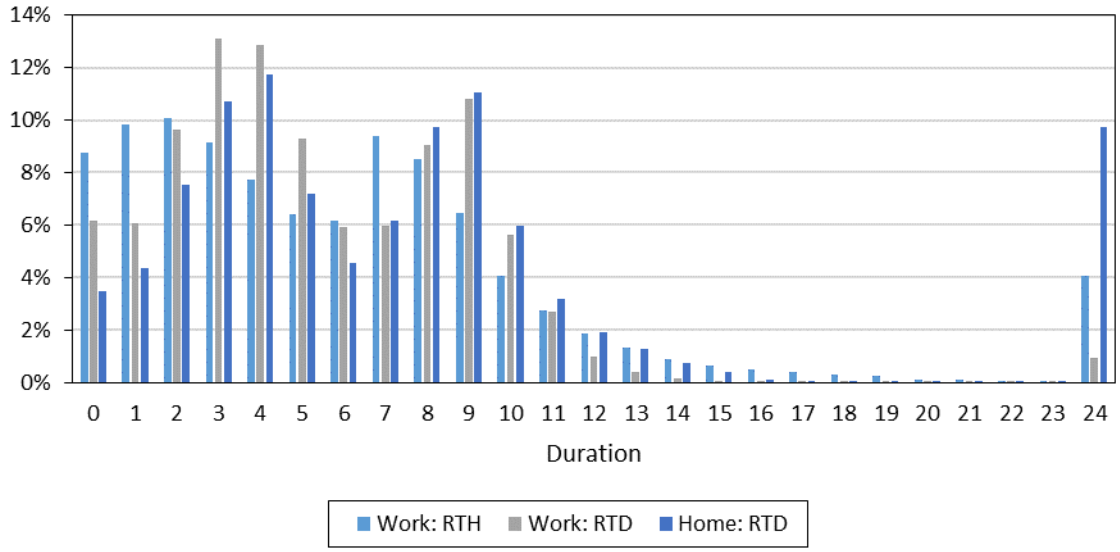



Figure 5.4 contains three panels summarizing the average session price, total kWh for the charging session, and session duration by location and who pays. The first panel shows the largest price variation for work / rate-to-host sessions.

**Figure 5.4: VGI Pilot Session Box-Whisker Plots for Price, Charge, and Duration**

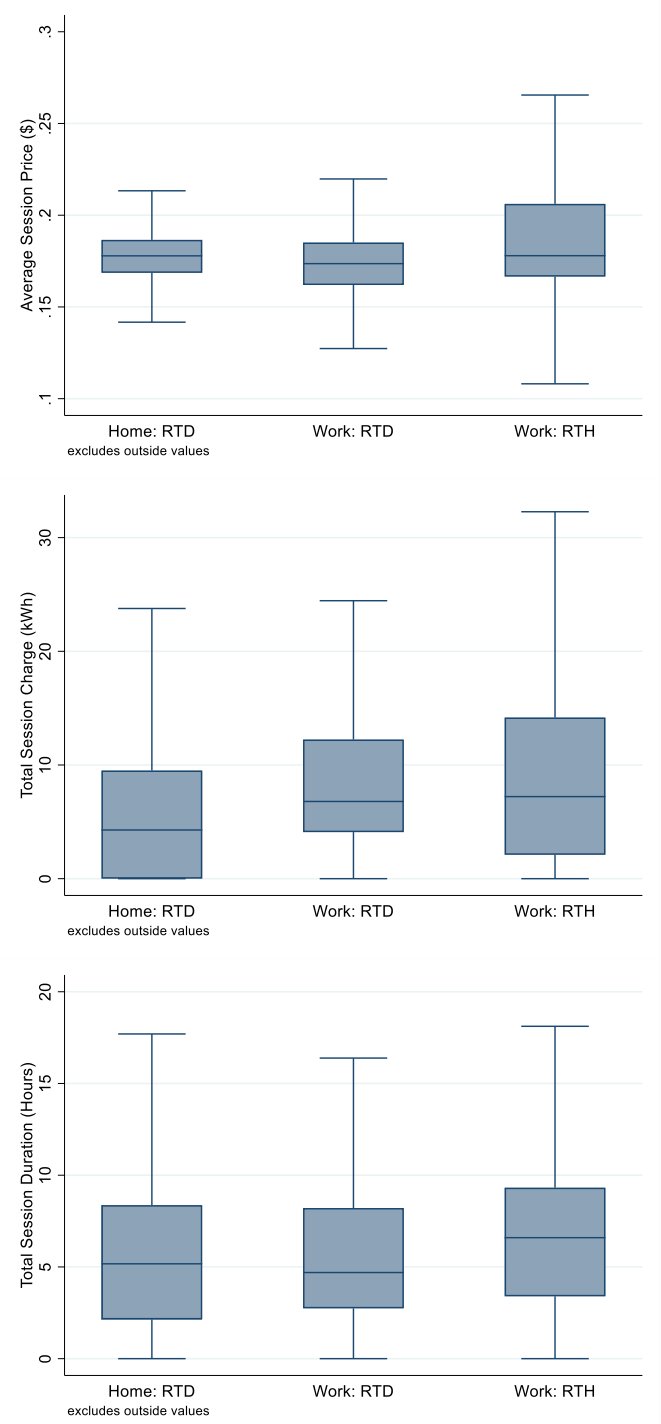



Table 5.2 presents the estimates associated with regression models described in Section 3.4. The estimates of primary interest are in the first two rows, showing the effect of variations in the price per kWh on the total kWh of the charging session (in the first set of columns) and the duration of the 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 -5.564 coefficient indicates that a 10 cents/kWh increase in price leads to a 0.5564 kWh reduction in energy charged during the session), but not with shorter charging durations (the -0.070 estimate is not statistically significantly different from zero).

In contrast, the "Work" estimates show a *positive* price effect for rate-to-host charging sessions (the 2.541 kWh estimate and the 1.824 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 2.541 + (-6.628) = -4.087. This means that a 10 cents/kWh increase in price reduces charged kWh by 0.4087. The duration model indicates that the price effect is not different for rate-to-host and rate-to-driver sessions, as evidenced by the -0.243 coefficient that is not statistically significantly different from zero.

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.

**Table 5.2: VGI Regression Results**

| Variable | kWh | | Duration | |
|---|---|---|---|---|
| | Work | Home | Work | Home |
| Actual Price ($) | 2.541*** | -5.564*** | 1.824*** | -0.070 |
| | (0.000) | (0.000) | (0.000) | (0.826) |
| Actual Price X RTD | -6.628*** | n/a | -0.243 | N/a |
| | (0.000) | | (0.601) | |
| Mean 17 | -0.033*** | 0.053*** | -0.021*** | 0.023*** |
| | (0.000) | (0.002) | (0.000) | (0.003) |
| Start Hour FE | Y | Y | Y | Y |
| Driver FE | Y | Y | Y | Y |
| Station FE | Y | Y | Y | Y |
| Observations | 162,503 | 35,463 | 162,503 | 35,463 |
| R-squared | 0.372 | 0.341 | 0.576 | 0.532 |

Robust p-value in parentheses

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

# 6. *Ex-Ante* Load Impacts

This section describes the development 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.

The first part of the section describes the methodologies used, followed by a presentation of the resulting forecasts. *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 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.

## *6.1 Methodology*

### 6.1.1 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 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.

### 6.1.2 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 the period of October 2018 through September 2019 for customers on both rates. Customers are first sorted as weather sensitive or not.[28] Regression models were estimated separately for each hour of the day, by weather sensitivity, using daily observations for weekdays, and a form similar to 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;

[28] 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.

- Weather variables were included (Mean17, CDD65, HDD65, and HDH65)[29];
- 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 TOU 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 TOU load impacts from the *ex-post* analysis.[30] 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.

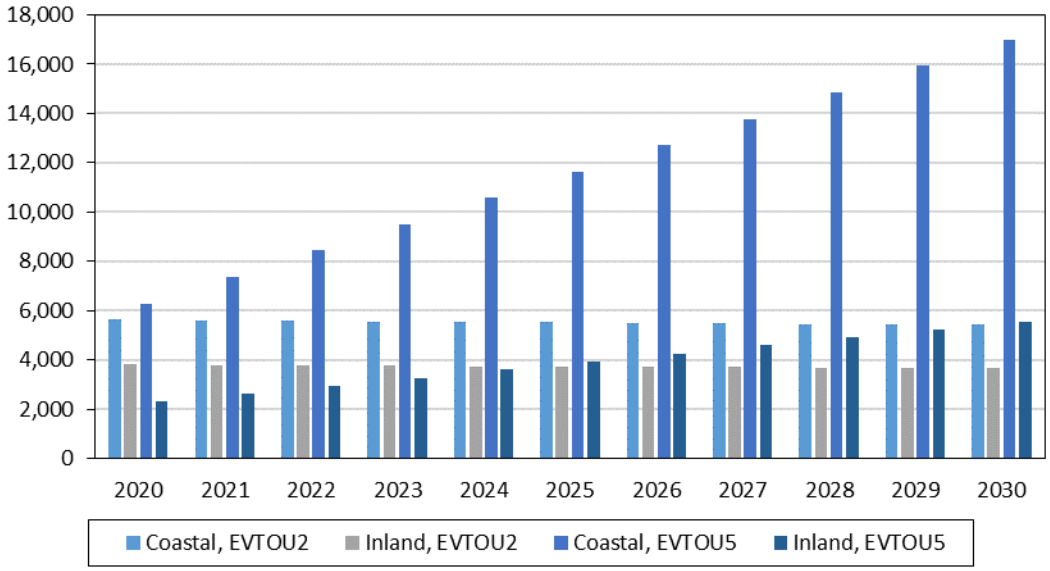
### 6.1.3 Enrollment forecast

Figure 6.1 shows SDG&E's enrollment forecasts for the EVTOU2 and EVTOU5 rates. Enrollment is anticipated to decline slightly over time for EVTOU2, while enrollment in EVTOU5 is forecasted to nearly triple among coastal customers by the end of the forecast period. EVTOU5 load impact enrollment is expected to be much greater in the Coastal climate zone than in the Inland.

[29] 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).

[30] 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**




## *6.2 Ex-Ante load impacts – Residential EVTOU2*

This subsection summarizes the *ex-ante* TOU peak load impact forecasts for customers anticipated to be enrolled in the EVTOU2 residential rate. Figure 6.2 shows aggregate loads and load impacts for EVTOU2 customers, in 2021 for an August SDG&E 1-in-2 average weekday. The average peak load impact is 2 percent of the reference load.

**Figure 6.2: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU2 Customers,* (*August 2021 SDG&E 1-in-2 Average Weekday*)**

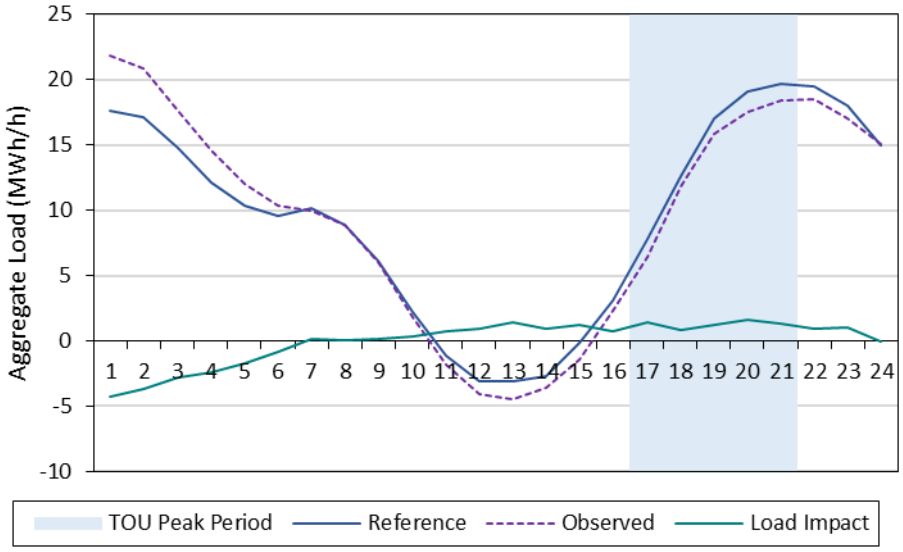


Figure 6.3 shows the monthly distributions of the peak-period TOU load impacts (TOU peak period aligns with the RA window) for EVTOU2 customers. Load impacts are greatest in the summer months, particularly July, August, and September. Results for the winter months are somewhat smaller. The two spring months, March and April, yield the lowest load impact. 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, of the summer rate schedule.

**Figure 6.3: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU2 Customers,* (*2021 SDG&E 1-in-2 Average Weekday,* RA Window)**

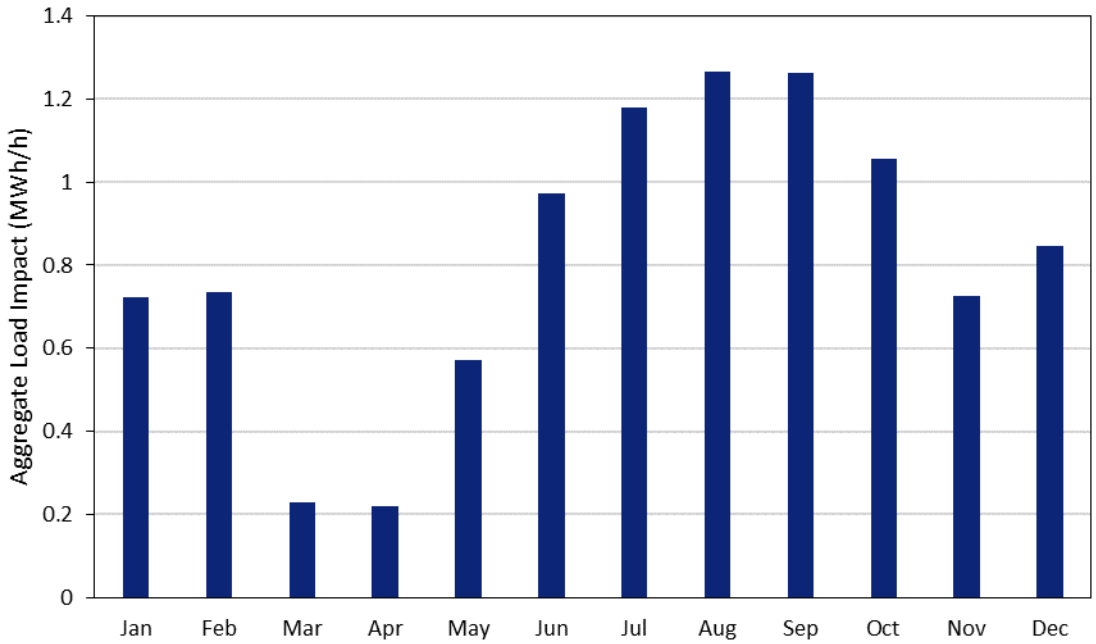
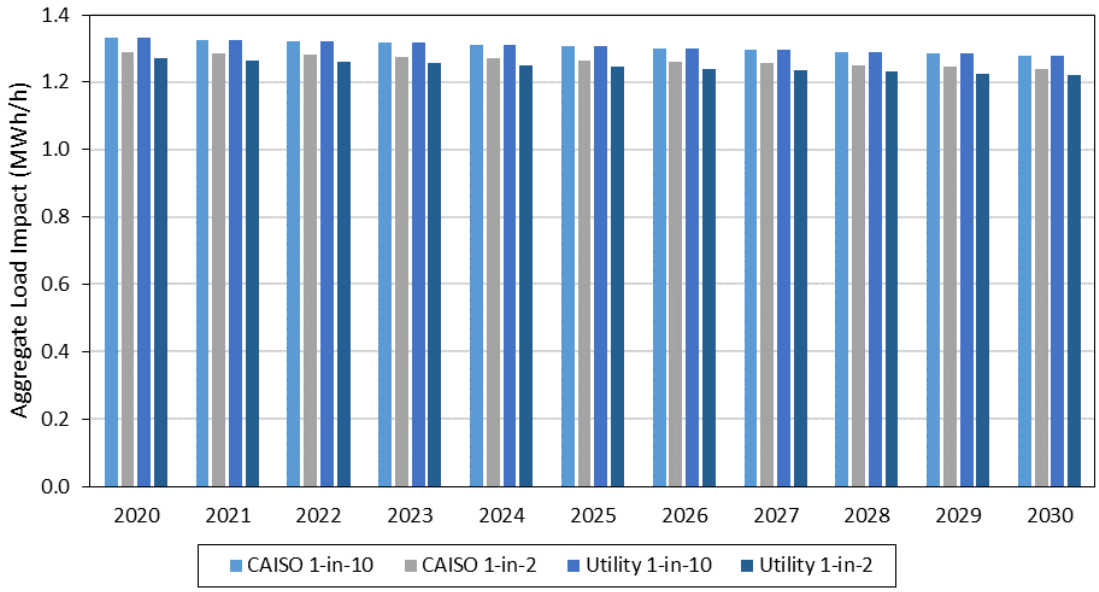



Figure 6.4 shows the aggregate average August weekday TOU load impacts over the forecast period, differentiated by weather scenario. The load impacts are largest for the CAISO and Utility 1-in-10 scenarios, which have equivalent temperatures for the average August weekday. (TOU load impacts are largest for the Utility 1-in-10 scenarios on monthly peak days.) The decrease of enrollment numbers over time drives aggregate impacts lower each year.

**Figure 6.4: Aggregate TOU Load Impacts (MWh/h) – *EVTOU2* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)**




## *6.3 Ex-Ante load impacts – Residential EVTOU5*

This subsection summarizes the *ex-ante* TOU peak load impact forecasts for customers anticipated to be enrolled in the EVTOU5 rate. Figure 6.5 shows aggregate loads and load impacts for EVTOU5 customers, in 2021 for an August SDG&E 1-in-2 average weekday. The average peak load impact is 22 percent of the reference load.

**Figure 6.5: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *EVTOU5 Customers,* (*August 2021 SDG&E 1-in-2 Average Weekday*)**

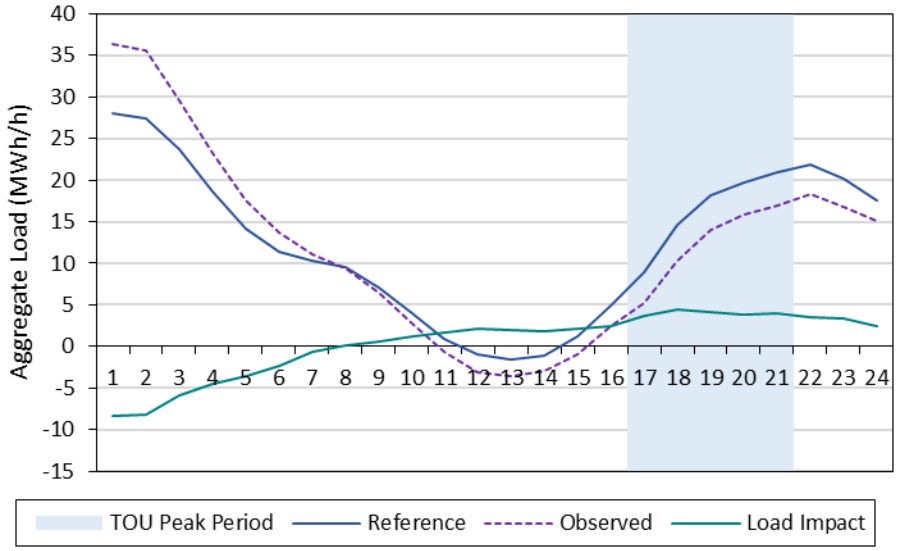


Figure 6.6 shows the monthly distributions of the peak-period TOU load impacts (TOU peak period aligns with the RA window) for EVTOU5 customers. Load impacts are greatest in December and November, even though peak period rates are higher in the summer than in winter months. Spring months exhibit the lowest peak period load impacts.

**Figure 6.6: Aggregate TOU Load Impacts (MWh/h) by Month – *EVTOU5 Customers,* (*2021 SDG&E 1-in-2 Average Weekday,* RA Window)**

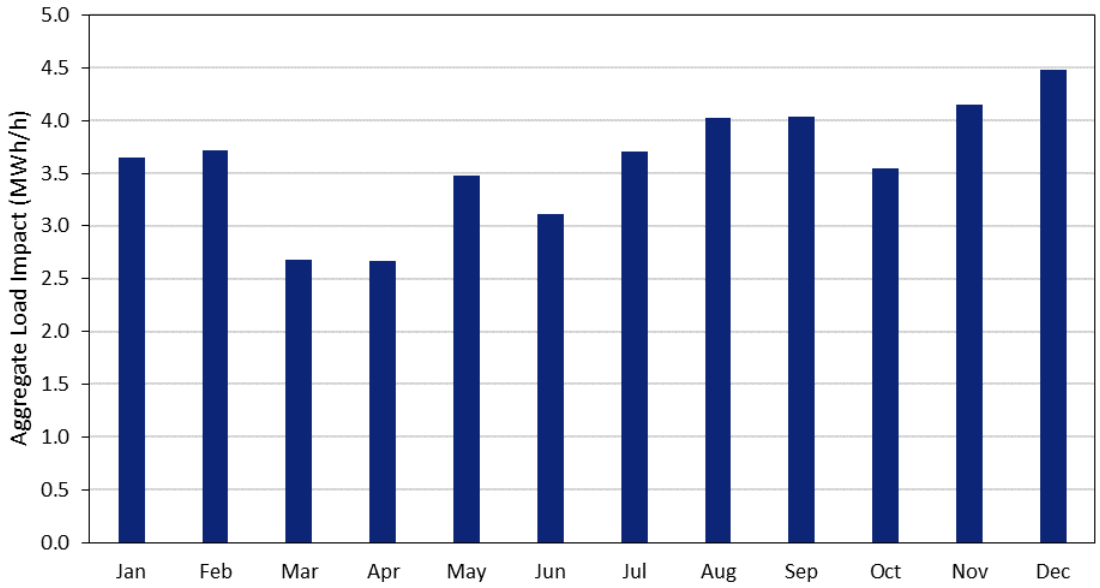
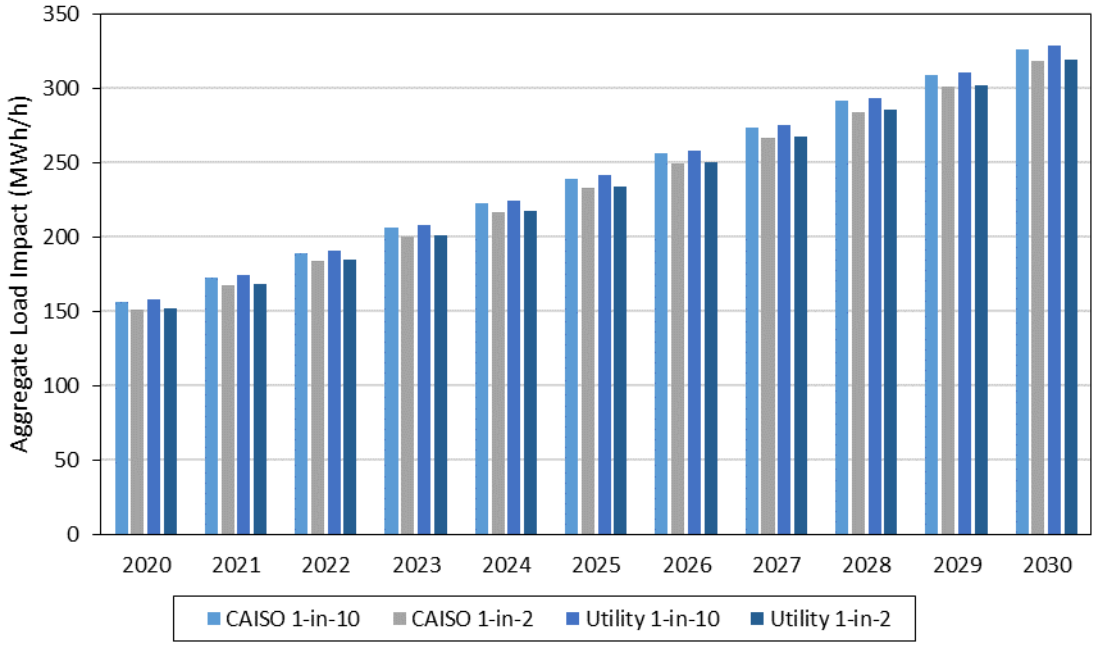



Figure 6.7 shows the aggregate average August weekday TOU load impacts over the forecast period, differentiated by weather scenario. The load impacts are largest for the CAISO and Utility 1-in-10 scenarios, which have equivalent temperatures for the average August weekday. (TOU load impacts are largest for the Utility 1-in-10 scenarios on monthly peak days.) Whereas enrollment in EVTOU2 is expected to decline over the next decade, enrollment in EVTOU5 is expected to climb, which drives the annual increases in aggregate load impact during the RA window.

**Figure 6.7: Aggregate TOU Load Impacts (MWh/h) – *EVTOU5* Customers, by Year and Weather Scenario (*Average August Weekday, RA Window*)**




# 7. Comparisons of Results

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

Since no analysis exists prior to the current study period, there are no previous results to reconcile for customers who enrolled on EVTOU2 or EVTOU2. Therefore, the only comparison is the current study's *ex-post* versus *ex-ante* EVTOU load impacts.

## 7.1 Current *ex-post* versus current *ex-ante* for EVTOU2 Customers

Table 7.1 compares EVTOU2 customers' PY2019 *ex-post* TOU load impacts for the August and January average weekday with the corresponding *ex-ante* forecast for 2020 (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 changes in the number of customers, which is forecasted to grow between 2019 and 2020.

**Table 7.1: Comparison of Current *Ex-Post* and *Ex-Ante* TOU Load Impacts for EVTOU2 Customers**

| Season | Result | *Ex-post for 2019 Avg. Weekday from PY2019 Study* | *Ex-ante for 2020 Avg. Weekday from PY2019 Study* |
|---|---|---|---|
| **Summer (August)** | # Enrolled | 8,114 | 9,445 |
| | Reference (MWh/h) | 13.18 | 15.34 |
| | Load Impact (MWh/h) | 1.09 | 1.27 |
| | Per-customer reference (kWh/h) | 1.62 | 1.62 |
| | Per-customer load impact (kWh/h) | 0.13 | 0.13 |
| | % Load Impact | 8% | 8% |
| | Temperature | 74.7 | 76.3 |
| **Winter (January)** | # Enrolled | 8,927 | 9,467 |
| | Reference (MWh/h) | 14.09 | 14.54 |
| | Load Impact (MWh/h) | 0.93 | 0.73 |
| | Per-customer reference (kWh/h) | 1.58 | 1.54 |
| | Per-customer load impact (kWh/h) | 0.10 | 0.08 |
| | % Load Impact | 6.6% | 5.0% |
| | Temperature | 56.2 | 59.4 |

## 7.2 Current *ex-post* versus current *ex-ante* for EVTOU5 Customers

Table 7.2 compares EVTOU5 customers' PY2019 *ex-post* TOU load impacts for the August and January average weekday with the corresponding *ex-ante* forecast for 2020 (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 changes in the number of customers, which is forecasted to grow between 2019 and 2020.

**Table 7.2: Comparison of Current *Ex-Post* and *Ex-Ante* TOU Load Impacts for EVTOU5 Customers**

| Season | Result | *Ex-post for 2019 Avg. Weekday from PY2019 Study* | *Ex-ante for 2020 Avg. Weekday from PY2019 Study* |
|---|---|---|---|
| **Summer (August)** | # Enrolled | 7,229 | 8,591 |
| | Reference (MWh/h) | 11.29 | 14.34 |
| | Load Impact (MWh/h) | 2.67 | 3.45 |
| | Per-customer reference (kWh/h) | 1.56 | 1.67 |
| | Per-customer load impact (kWh/h) | 0.37 | 0.40 |
| | % Load Impact | 24% | 24% |
| | Temperature | 75.2 | 76.6 |
| **Winter (January)** | # Enrolled | 3,219 | 7,777 |
| | Reference (MWh/h) | 5.24 | 12.95 |
| | Load Impact (MWh/h) | 1.22 | 2.96 |
| | Per-customer reference (kWh/h) | 1.63 | 1.67 |
| | Per-customer load impact (kWh/h) | 0.38 | 0.38 |
| | % Load Impact | 23.3% | 22.9% |
| | Temperature | 56.1 | 59.4 |

# 8. 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.

# 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**

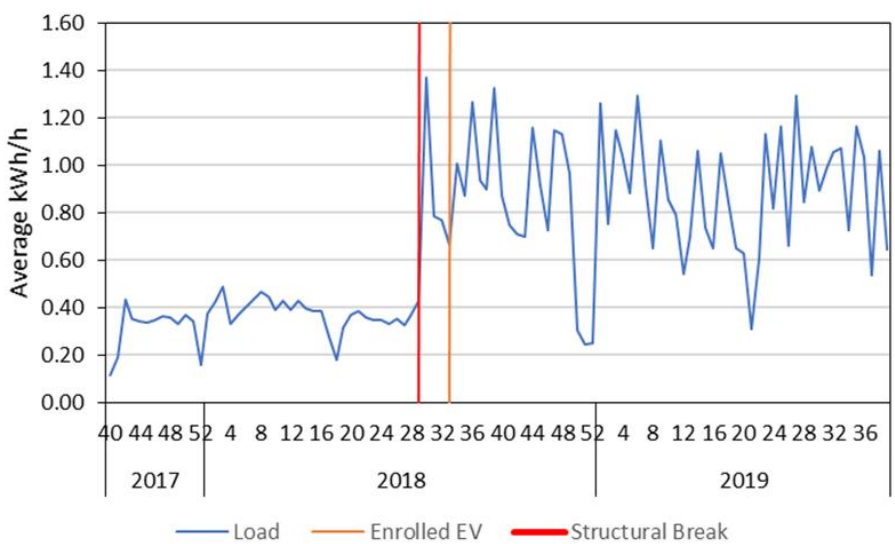


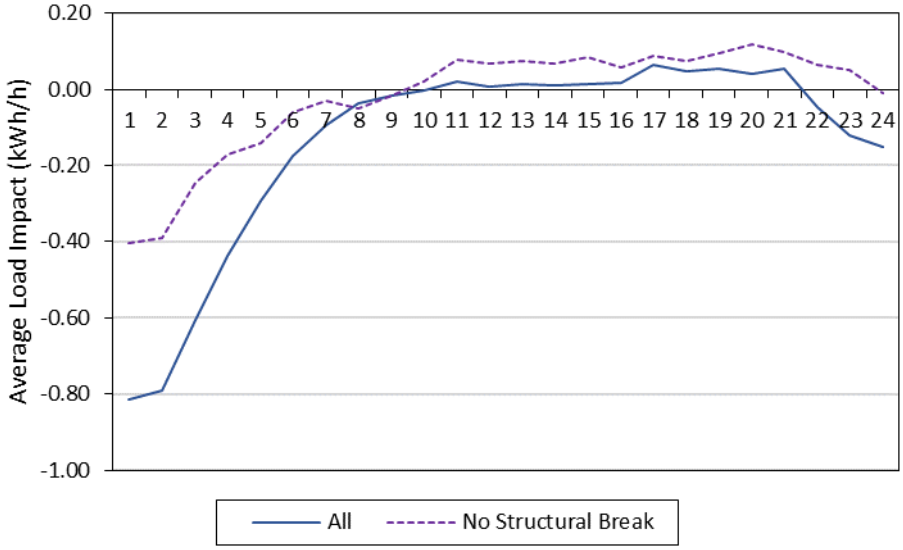
Table C.1 provides the resulting counts of EVTOU customers from the structural break tests. The "Removed" category represents the number of customers that were not included in the incremental EVTOU analysis because the structural break model indicated a statistically significant structural break. These 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 210 out of 836 EVTOU2 and 451 out of 3,023 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 | 469 | 2,067 |
| | Included | 144 | 350 |
| | **Total** | **613** | **2,417** |
| NEM | Removed | 157 | 505 |
| | Included | 66 | 101 |
| | **Total** | **223** | **606** |

*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 included customers that adopt 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 is about half for the "No Structural Break" customers than the version including all customers.

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



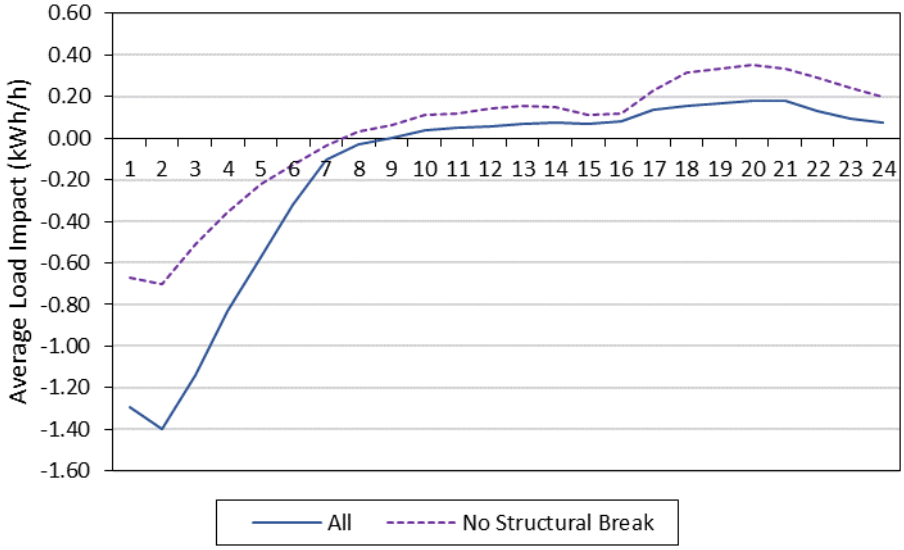


**Figure C.3: *Ex-post* Load Impacts for Non-NEM Incremental EVTOU5 Customers**