2015 Load Impact Evaluation of Pacific Gas and Electric Company's Mandatory Time-of-Use Rates for Small, Medium, and Agricultural Non-residential Customers: *Ex-post* and *Ex-ante* Report

Public Version

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Abstract

This report documents *ex-post* and *ex-ante* load impact evaluations for Pacific Gas and Electric Company's ("PG&E") mandatory time-of-use ("TOU") rates that were implemented for small-sized, medium-sized, and agricultural non-residential customers in 2015. The report provides: 1) estimates of *ex-post* load impacts for customers who recently transitioned to TOU rates prior to summer 2015 and 2) an *ex-ante* forecast of load impacts for 2016 through 2026 that is based on PG&E's enrollment forecasts and our *ex-post* load impact estimates.

PG&E's Schedule A-1 is an energy-only rate that applies to the smallest non-residential customers. Schedule A-10 is a demand and energy rate that applies to customers with maximum demand between 200 and 500 kW. Schedule AG-1 is a demand and energy rate that applies to customers with maximum demand typically below 200 kW and where at least 70 percent of annual energy consumption is for agricultural end-uses. The TOU rates under each tariff, which apply to customer accounts that have been transitioned to TOU, are seasonal tiered rates, with energy prices that differ by summer and winter seasons and by peak, part-peak, and off-peak time periods.

PG&E has been transitioning small and medium business (SMB) and agricultural customers to mandatory TOU rates since 2012, with cohorts of approximately 225,000 SMB customers transitioned in November 2012, and 144,000 in November 2013. Similarly, cohorts of 17,500 agricultural customer accounts were transitioned in March of 2013. The *ex-pos*t study presented here concerns customers transitioned to TOU rates in November 2014 and March 2015, of which there were 61,000 SMB and 8,300 agricultural customers. Approximately 75,000 customers who lacked necessary metering remained on non-TOU rates, but because of limited data and other unique characteristics, they cannot be used as a control group and are not included in any part of this study.

Estimating load impacts for non-event-based rates like TOU requires some form of before and after, or treatment and control group approach, or a combination of the two. In prior years, the availability of customers who had not yet transitioned to a TOU rate provided a pool of comparable control group customers and a difference-in-differences approach was used. In this study, a comparable control group is not available, therefore we are limited to estimating *ex-post* load impacts by comparing load data for treatment (TOU) customers before and after transitioning to TOU rates.

Using the new approach, we are able to control for differences in weather during the pre- and post-treatment periods, but we are unable to account for exogenous changes that a difference-in-differences approach can capture. As a result, our ability to attribute estimated load impacts to TOU rates is substantially limited. To investigate whether exogenous factors contributed to changes in energy consumption between 2014 and 2015 we also examine load data for previously transitioned TOU customers, specifically

those who were included in the previous year's analysis (*i.e.*, those transitioned in November 2013).

The following activities provide an overview of the approach used for this year's evaluation:

- We consider all AG-1 customers and random samples from the A-1 and A-10 customers who were newly transitioned to TOU rates in November 2014 (A-1 and A-10) or March 2015 (AG-1/AG-4);
- We perform model validation tests to identify the optimal weather variables to include in each customer group's models for summer and winter seasons;
- We estimate TOU load impacts by hour using fixed-effects panel regressions; and
- We compare 2015 load impact estimates for newly transitioned TOU customers to 2015 load impact estimates for customers that were transitioned to TOU in the prior year. This comparison provides context for current year load impact estimates.

Similar to last year's study (but in contrast to studies before that), we differentiate SMB customers by size group (*i.e.*, under 20 kW versus 20 to 200 kW) rather than tariff (*e.g.*, A-1 versus A-10). This was done to conform to the manner in which PG&E forecasts customer enrollments, and examines and reports its load impacts, which is by customer size.

Our *ex-post* load impact estimates show load reductions in response to TOU rates for small and medium customers in all pricing periods ranging from 0.3 to 3.4 percent. This pattern of load reductions in all periods is not consistent with the usual expectation of TOU demand response, which is that loads would decrease in the peak period (during which the price is higher relative to an equivalent flat rate) and increase in the off-peak period (during which the price is lower relative to an equivalent flat rate). The load impacts estimated here appear to be more consistent with all-hours conservation than a response to changing price signals by time of day.

In contrast, *ex-post* load impact estimates for agricultural customers are more in line with expected responses to TOU rates. That is, there are modest load increases (ranging from 0.4 to 1.0 percent) in off-peak periods and load reductions of 2.4 percent during the peak period.

Ex-ante load impacts were separately developed for two sets of non-residential customers:

- *Incremental customers*. This customer group consists of customers who will be transitioned to TOU rates in the coming years, or customers who will be new to PG&E and will be placed on a TOU rate by default. The load impacts for this group will affect PG&E's system load going forward.
- *Embedded customers*. These customers have been on TOU rates in the past, so their load impacts are embedded in PG&E's system load and will not lead to additional future load changes. The embedded customer group includes

customers who have been on TOU rates for many years as well as customers who were transitioned to TOU rates prior to the 2014 and 2015 program years.

Incremental customer TOU enrollments for SMB customers is approximately 39,000 in early 2016 (following the transition of customers in November 2015) and increase to approximately 76,000 by the end of 2017 (due to two transitions of agricultural customers and an additional transition of SMB customers). August peak day incremental TOU load impacts are approximately 10 MW in 2016 rising to approximately 26 MW by 2026.

In contrast to the incremental TOU load impact forecast, the *embedded* TOU load impact forecast remains constant across the forecast years. Two types of customers are present in the embedded TOU load impact forecast: customers who have been on TOU rates for many years (typically large customers on E-19 or E-20 tariffs) and customers who have been transitioned to TOU rates in recent years.

There are 480,000 service accounts in our embedded TOU load impact forecast. Of these, 80,000 represent recently transitioned service accounts while the remainder are customers who have been on TOU rates for many years. Embedded TOU load impacts range from 300 to 350 MW in summer months and are approximately 55 MW in winter months.

Executive Summary

This report documents *ex-post* and *ex-ante* load impact evaluations for Pacific Gas and Electric Company's ("PG&E") mandatory time-of-use ("TOU") rates that were implemented for small-sized, medium-sized, and agricultural non-residential customers in 2015. The report provides: 1) estimates of *ex-post* load impacts for customers who newly transitioned to TOU rates prior to summer 2015 and 2) an *ex-ante* forecast of load impacts for 2016 through 2026 that is based on PG&E's enrollment forecasts and our *ex-post* load impact estimates.

The primary research questions addressed by this evaluation are:

1. What were the non-residential TOU load impacts for customers transitioned in late 2014 and early 2015?
2. How were the load impacts distributed across industry groups?
3. How were the load impacts distributed across CAISO local capacity areas?
4. What are the *ex-ante* load impacts for 2016 through 2026?

ES.1 Resources covered

PG&E's Schedule A-1 is an energy-only rate that applies to the smallest non-residential customers. Schedule A-10 is a demand and energy rate that applies to customers with maximum demand between 200 and 500 kW. Schedule AG-1 is a demand and energy rate that applies to customers with maximum demand typically below 200 kW and where at least 70 percent of annual energy consumption is for agricultural end-uses. The TOU rates under each tariff, which apply to customer accounts that have been transitioned to TOU, are seasonal tiered rates, with energy prices that differ by summer and winter seasons and by peak, part-peak, and off-peak time periods.

PG&E has been transitioning small and medium business (SMB) and agricultural customers to mandatory TOU rates since 2012, with cohorts of approximately 225,000 SMB customers transitioned in November 2012, and 144,000 in November 2013. Similarly, cohorts of 17,500 agricultural customer accounts were transitioned in March of 2013. The *ex-pos*t study presented here concerns customers transitioned to TOU rates in November 2014 and March 2015, of which there were 61,000 SMB and 8,300 agricultural customers. Approximately 75,000 customers who lacked necessary metering remained on non-TOU rates, but because of limited data and other unique characteristics, they cannot be used as a control group and are not included in any part of this study.

ES.2 Evaluation Methodology

Estimating load impacts for non-event-based rates like TOU requires some form of before and after, or treatment and control group approach, or a combination of the two. In prior years, the availability of customers who had not yet transitioned to a TOU rate provided a pool of comparable control group customers and a difference-in-differences approach was used. In this study, a comparable control group is not available, therefore we are limited to estimating *ex-post* load impacts by comparing load data for treatment (TOU) customers before and after transitioning to TOU rates.

Using the new approach, we are able to control for differences in weather during the pre- and post-treatment periods, but we are unable to account for exogenous changes that a difference-in-differences approach can capture. As a result, our ability to attribute estimated load impacts to TOU rates is substantially limited. To investigate whether exogenous factors are contributing to changes in energy consumption between 2014 and 2015 we also examine load data for previously transitioned TOU customers, specifically those who were included in the previous year's analysis (*i.e.*, those transitioned in November 2013).

The following activities provide an overview of the approach used for this year's evaluation:

- We consider all AG-1 customers and random samples from the A-1 and A-10 customers who were newly transitioned to TOU rates in November 2014 (A-1 and A-10) or March 2015 (AG-1/AG-4);
- We perform model validation tests to identify the optimal weather variables to include in each customer group's models for summer and winter seasons;
- We estimate TOU load impacts by hour using fixed-effects panel regressions; and
- We compare 2015 load impact estimates for newly transitioned TOU customers to 2015 load impact estimates for customers that were transitioned to TOU in the prior year. This comparison provides context for current year load impact estimates.

Similar to last year's study (but in contrast to studies before that), we differentiate SMB customers by size group (*i.e.*, under 20 kW versus 20 to 200 kW) rather than tariff (*e.g.*, A-1 versus A-10). This was done to conform to the manner in which PG&E forecasts customer enrollments, and examines and reports its load impacts, which is by customer size.

ES.3 Ex-post Load Impacts

Our *ex-post* load impact estimates show load reductions in response to TOU rates for small and medium customers in all pricing periods ranging from 0.3 to 3.4 percent. This pattern of load reductions in all periods is not consistent with the usual expectation of TOU demand response, which is that loads would decrease in the peak period (during which the price is higher relative to an equivalent flat rate) and increase in the off-peak period (during which the price is lower relative to an equivalent flat rate). The load impacts estimated here appear to be more consistent with all-hours conservation than a response to changing price signals by time of day.

In contrast, *ex-post* load impact estimates for agricultural customers are more in line with expected responses to TOU rates. That is, there are modest load increases (ranging from 0.4 to 1.0 percent) in off-peak periods and load reductions of 2.4 percent during the peak period.

Table ES.1: Small and Medium Business Customer Estimated TOU Load Impacts

<table>
<tr><th colspan="3" rowspan="2">TOU Pricing Period</th><th colspan="3">% Load Change:</th></tr>
<tr><th>Small Business (Under 20kW)</th><th>Medium Business (20-200kW)</th><th>Agricultural Business</th></tr>
<tr><td rowspan="4">Summer</td><td rowspan="3">Weekdays</td><td>Peak</td><td>-2.9%</td><td>-2.1%</td><td>-2.4%</td></tr>
<tr><td>Part-Peak</td><td>-2.6%</td><td>-1.8%</td><td>--</td></tr>
<tr><td>Off-Peak</td><td>-2.1%</td><td>-1.3%</td><td>1.0%</td></tr>
<tr><td>Weekends & Holidays</td><td>Off-Peak</td><td>-2.4%</td><td>-1.5%</td><td>0.4%</td></tr>
<tr><td rowspan="3">Non-Summer</td><td rowspan="2">Weekdays</td><td>Part-Peak</td><td>-2.4%</td><td>-0.5%</td><td>--</td></tr>
<tr><td>Off-Peak</td><td>-2.4%</td><td>-0.3%</td><td>--</td></tr>
<tr><td>Weekends & Holidays</td><td>Off-Peak</td><td>-3.4%</td><td>-0.9%</td><td>--</td></tr>
</table>

ES.4 Ex-ante Load Impacts

Ex-ante load impacts were separately developed for two sets of non-residential customers:

- *Incremental customers*. This customer group consists of customers who will be transitioned to TOU rates in the coming years, or customers who will be new to PG&E and will be placed on a TOU rate by default. The load impacts for this group will affect PG&E's system load going forward.
- *Embedded customers*. These customers have been on TOU rates in the past, so their load impacts are embedded in PG&E's system load and will not lead to additional future load changes. The embedded customer group includes customers who have been on TOU rates for many years as well as customers who were transitioned to TOU rates prior to the 2013 and 2014 program years.

Incremental TOU load impacts

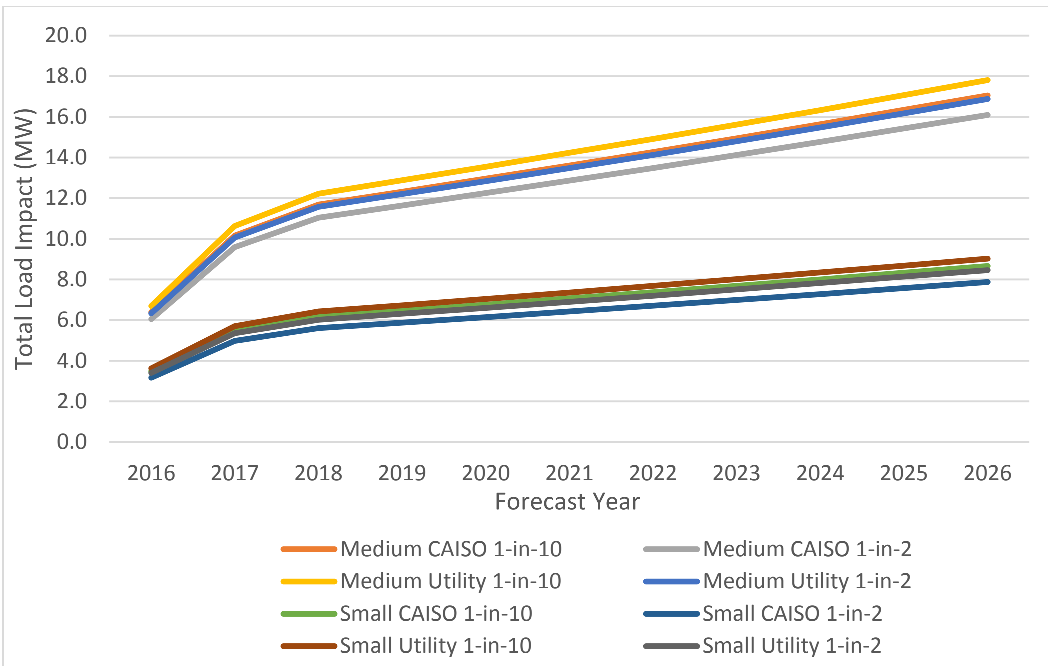
There are three sources of incremental TOU load impacts in the forecast period:

- Transitions of SMB customers in November 2015 and November 2016;
- Transitions of agricultural customers in March 2016 and March 2017; and
- The addition of new customers over time, which are now defaulted directly to TOU rates.

In each of these cases, *ex-post* load impacts serve as the basis for the per-customer load impacts within size group and LCA. For the SMB customers, we use the 2015 *ex-post* load impacts associated with customers transitioned in November 2014. For agricultural customers, we use the 2015 *ex-post* load impacts estimated for customers transitioned in March 2015.

Incremental customer TOU enrollments for SMB customers is approximately 39,000 in early 2016 (following the transition of customers in November 2015) and increase to approximately 76,000 by the end of 2017 (due to two transitions of agricultural customers and an additional transition of SMB customers). Figure ES.1 shows the hourly incremental load impact for each August in the forecast period, for each weather scenario and small and medium customer groups. Incremental load impacts for agricultural customers (not pictured) are approximately 0.3 MW in August 2016 and rise to 1.1 MW after the March 2017 transition to TOU rates and remain constant going forward.

Figure ES.1: August Peak Day *Ex-ante* Incremental TOU Load Impacts by Group and Weather Scenario



Embedded TOU load impacts

In contrast to the incremental TOU load impact forecast, the embedded TOU load impact forecast remains constant across the forecast years. That is, there is assumed to be a set of currently enrolled customers that have embedded TOU load impacts (meaning they are already reflected in the customer's load profile and, by extension, PG&E's system load profile), and those load impacts are carried forward through the forecast period.

Two types of customers are present in the embedded TOU load impact forecast: customers who have been on TOU rates for many years (typically large customers on

E-19 or E-20 tariffs) and customers who have been transitioned to TOU rates in recent years. A description of our *ex-ante* methods for each group follows.

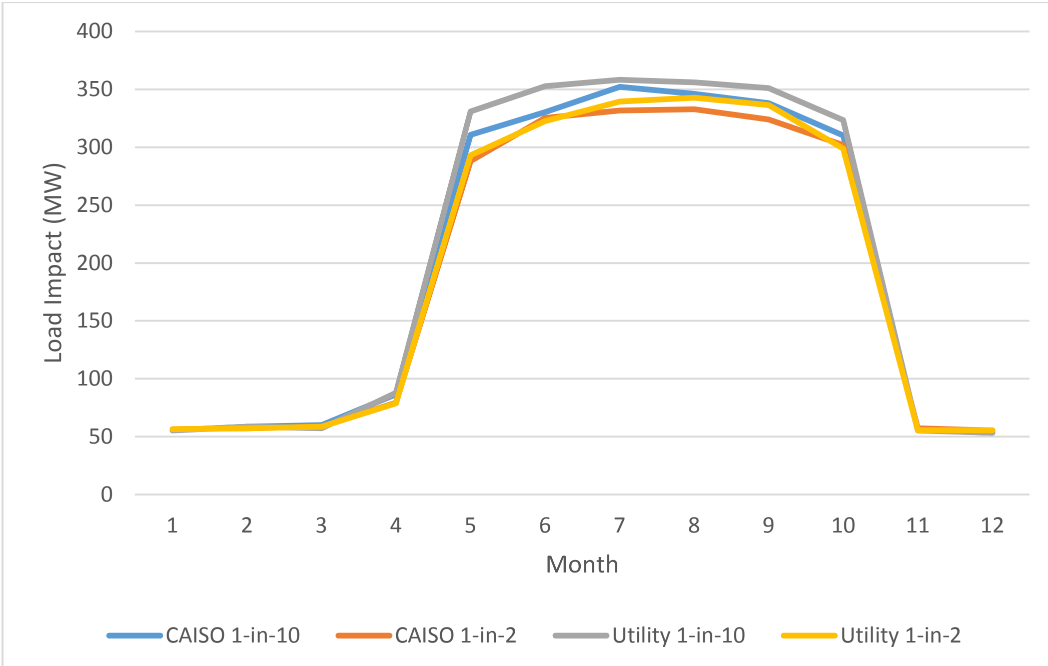
For the customers who have been on TOU rates for many years, we cannot estimate *ex-post* load impacts because these customers have not been observed on non-TOU rates. Therefore, load impacts for these customers have been simulated using existing studies of TOU demand response. For consistency across studies, we have carried forward the analysis of these customers from previous studies (conducted following the 2013 and 2014 program year). When evaluating the 2014 program year, we needed to adjust the 2013 forecast to account for changes in the *ex-ante* weather scenarios. That is, PG&E updated its 1-in-2 and 1-in-10 weather definitions prior to that analysis and also added scenarios that correspond to CAISO-coincident conditions. These adjustments were made by adjusting the cell-specific load profiles to account for differences in *ex-ante* weather conditions, where the amount of the adjustment is based on cell-specific estimates of the effect of weather (daily cooling and heating degree hours) on loads.

For the recently transitioned customers, the *ex-ante* load impacts are based on our SMB *ex-post* forecast for customers transitioned in November 2014. The methods follow those used to develop the incremental TOU load impact forecast described in Section 7.1, but applying a different set of enrollments.

There are 480,000 service accounts in our embedded TOU load impact forecast. Of these, 80,000 represent recently transitioned service accounts while the remainder are customers who have been on TOU rates for many years.

Figure ES.2 shows the monthly embedded TOU load impacts for each weather scenario. The load impacts are averaged across 1:00 to 6:00 p.m. for April through October and 4:00 to 9:00 p.m. for November through March. Summer load impacts range from 300 to 350 MW and winter load impacts are approximately 55 MW. As expected, the utility-specific 1-in-10 peak day load impacts are the highest in the summer.

Figure ES.2: Embedded TOU Load Impacts by Month and Weather Scenario



1. Introduction and Purpose of the Study

This report documents *ex-post* and *ex-ante* load impact evaluations for Pacific Gas and Electric Company's ("PG&E") mandatory time-of-use ("TOU") rates that were implemented for small-sized, medium-sized, and agricultural non-residential customers in 2015. The report provides: 1) estimates of *ex-post* load impacts for customers who newly transitioned to TOU rates prior to summer 2015 and 2) an *ex-ante* forecast of load impacts for 2016 through 2026 that is based on PG&E's enrollment forecasts and our *ex-post* load impact estimates.

The primary research questions addressed by this evaluation are:

1. What were the non-residential TOU load impacts for customers transitioned in late 2014 and early 2015?
2. How were the load impacts distributed across industry groups?
3. How were the load impacts distributed across CAISO local capacity areas?
4. What are the *ex-ante* load impacts for 2016 through 2026?

The report is organized as follows. Section 2 contains a description of the TOU rates and the transition process; Section 3 describes the methods used in the study; Sections 4 through 6 contain detailed *ex-post* load impact results for *small*, *medium*, and *agricultural* commercial and industrial customers transitioned in late 2014 and early 2015, respectively; Section 7 describes the *ex-ante* load impact forecast; Section 8 contains descriptions of differences in various scenarios of *ex-post* and *ex-ante* load impacts; and Section 9 provides recommendations. Appendix A contains an assessment of the validity of the study.

2. Description of the Rates and Transition Process

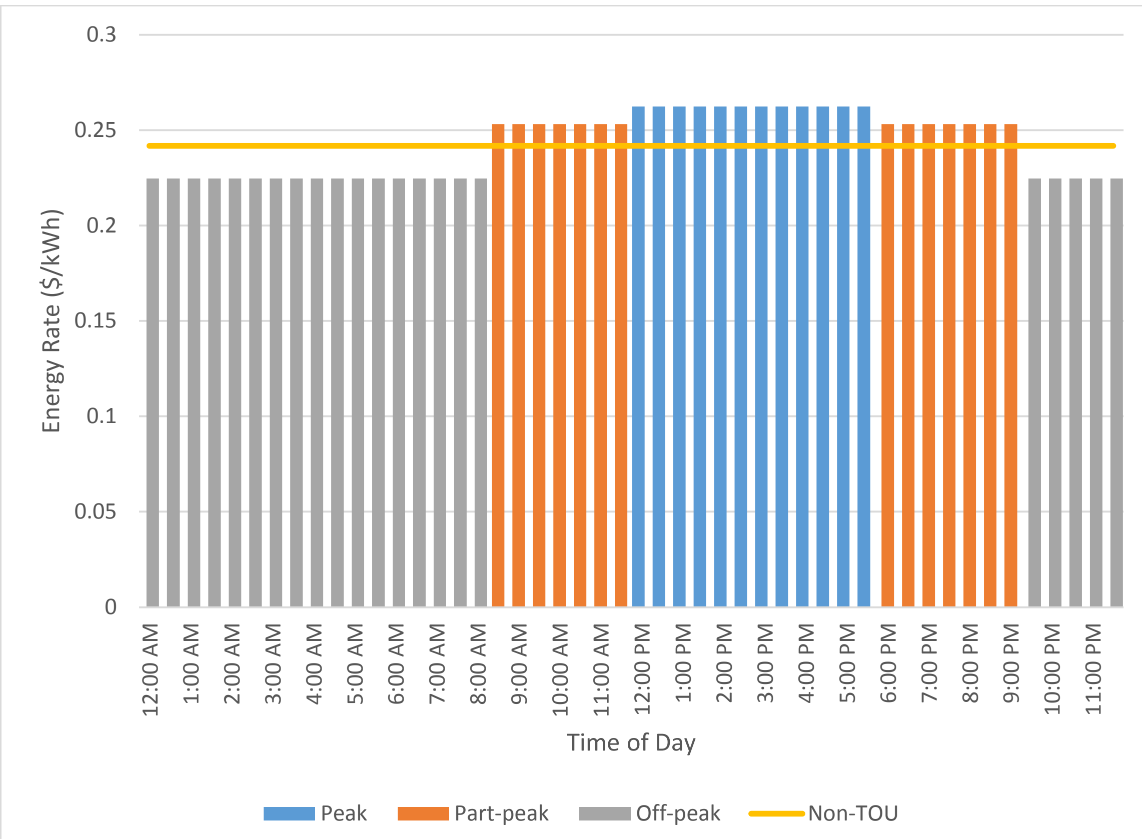
This section provides details on the relevant non-residential TOU rates and the process used to transition customers to those rates. Included in this study are small and medium business customers, which PG&E defines as customer accounts with maximum demands of less than 20 kW (small) and 20 to 200 kW (medium). The majority of these customers fall under Schedule A-1, while some of the larger accounts fall under A-10. Small non-residential agricultural customers who transitioned from the AG-1 rate to the AG-4 TOU rate are also included.

2.1 TOU Rate Descriptions

PG&E's Schedule A-1 is an energy-only rate that applies to the smallest non-residential customers. Schedule A-10 is a demand and energy rate that applies to customers with maximum demand between 200 and 500 kW. Schedule AG-1 is a demand and energy rate that applies to customers with maximum demand typically below 200 kW and where at least 70 percent of annual energy consumption is for agricultural end-uses. The TOU rates under each tariff, which apply to customer accounts that have been transitioned to TOU, are seasonal tiered rates, with energy prices that differ by summer and winter seasons and by peak, part-peak, and off-peak time periods.[1]

Figure 2.1 illustrates the TOU and non-TOU energy prices ($/kWh) that apply in summer months for the A-1 tariff (the winter rate does not have a peak period).[2] The figure shows the timing of the TOU periods, including the split morning and evening part-peak periods, as well as the level of prices in each period. As shown in the figure, the TOU price differentials relative to the non-TOU price (horizontal straight line) are relatively small. The peak and part-peak prices are 9 percent and 5 percent greater than the non-TOU price, respectively, while the off-peak price is 7 percent lower. Such small price differentials provide relatively small incentives to customers to reduce or shift load from peak and part-peak periods.

Figure 2.1: Summer TOU and Non-TOU Energy Prices by Time Period – *A-1*



The non-TOU version of the A-10 tariff has a flat energy price, while the TOU version has the same type of seasonal, three-tier energy prices as the A-1 tariff. However, both versions also have demand charges ($/kW) that apply to the customer's maximum

[1] The TOU tariffs define the summer period as May through October and the winter period as November through April. The AG-4 agriculture TOU rate does not have a part-peak period in the summer season.
[2] Prices effective June 1, 2015 to August 31, 2015.

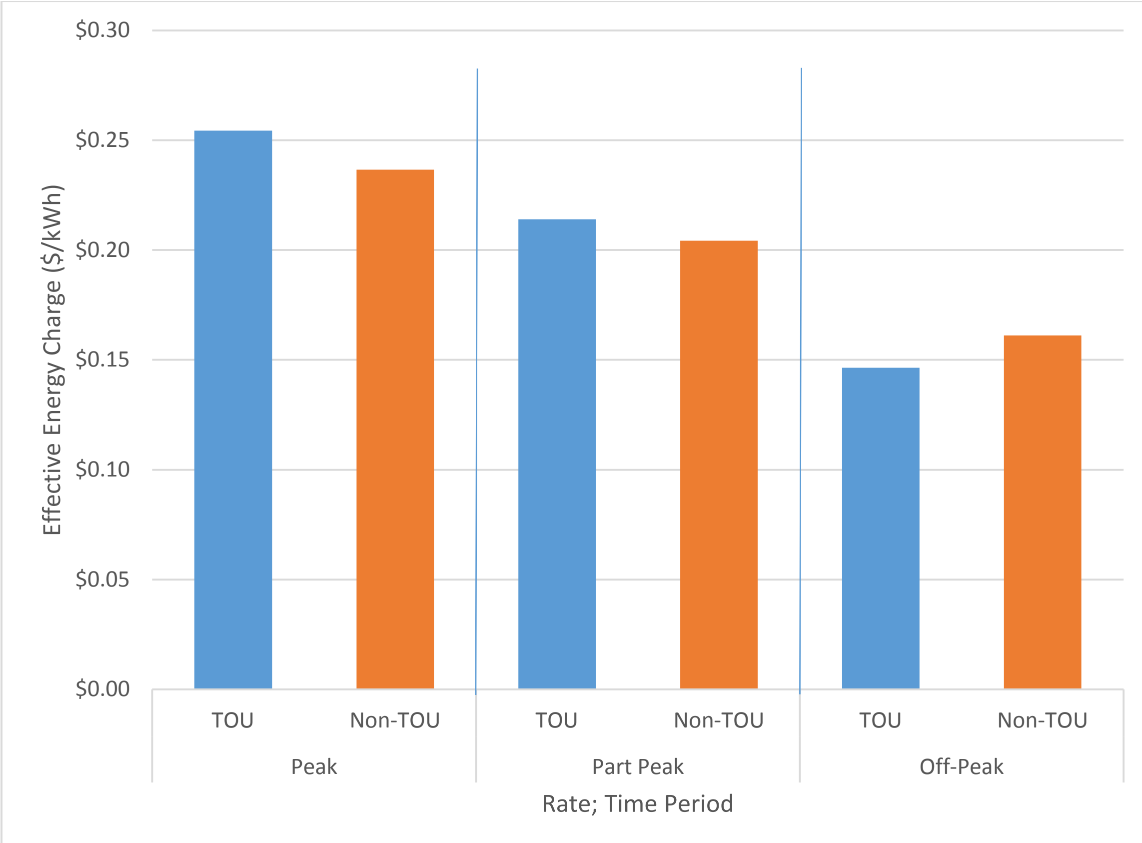
demand.[3] To provide a single metric for comparing the two versions of the A-10 tariff, it is useful to convert the demand charge into an "effective energy charge", or EEC, which may then be added to the energy charges. The EEC concept follows the logic that even though the demand charge is nominally applied to the single hour of highest demand in a month, the customer is uncertain about when that hour will occur, which effectively converts the identification of the hour of maximum demand into a probabilistic event.

From customers' perspectives, the hour of maximum demand is most likely to occur sometime during the time period in which their hourly load tends to be greatest. As an approximation, for most customers, that is most likely to occur during the peak period, or, somewhat less likely, in the part-peak period. For purposes of illustration, we assume that the hour of maximum demand is equally likely to occur in any hour of either the peak or part-peak period, and that it is more likely (60%) to occur in the peak rather than part-peak period. After "spreading" the demand charge across the peak and part-peak period under those assumptions, and adding the energy prices, we obtain the pattern of effective energy charges shown in Figure 2.2.

Note first that after accounting for the likelihood of setting the maximum demand in particular hours, even the *non-TOU* version of the A-10 tariff has an EEC that varies by time period. Because the energy prices under the *TOU version* vary by time period, that version has somewhat greater variation across time periods than the non-TOU version, in a pattern somewhat like that for A-1. Also like A-1, the differentials between the peak and part-peak EECs for the TOU and non-TOU versions are modest (8 percent and 5 percent for the peak and part-peak periods respectively).

[3] The same demand charges are applied under non-TOU and TOU versions of the A-10 tariff. Demand charges vary by voltage level. The secondary voltage demand charge is $16.23 per kW in the summer period and $8.00 in the winter period (effective June 1, 2015 to August 31, 2015).

Figure 2.2: Summer TOU and Non-TOU *Effective Energy Charges* by Time Period – *A-10*



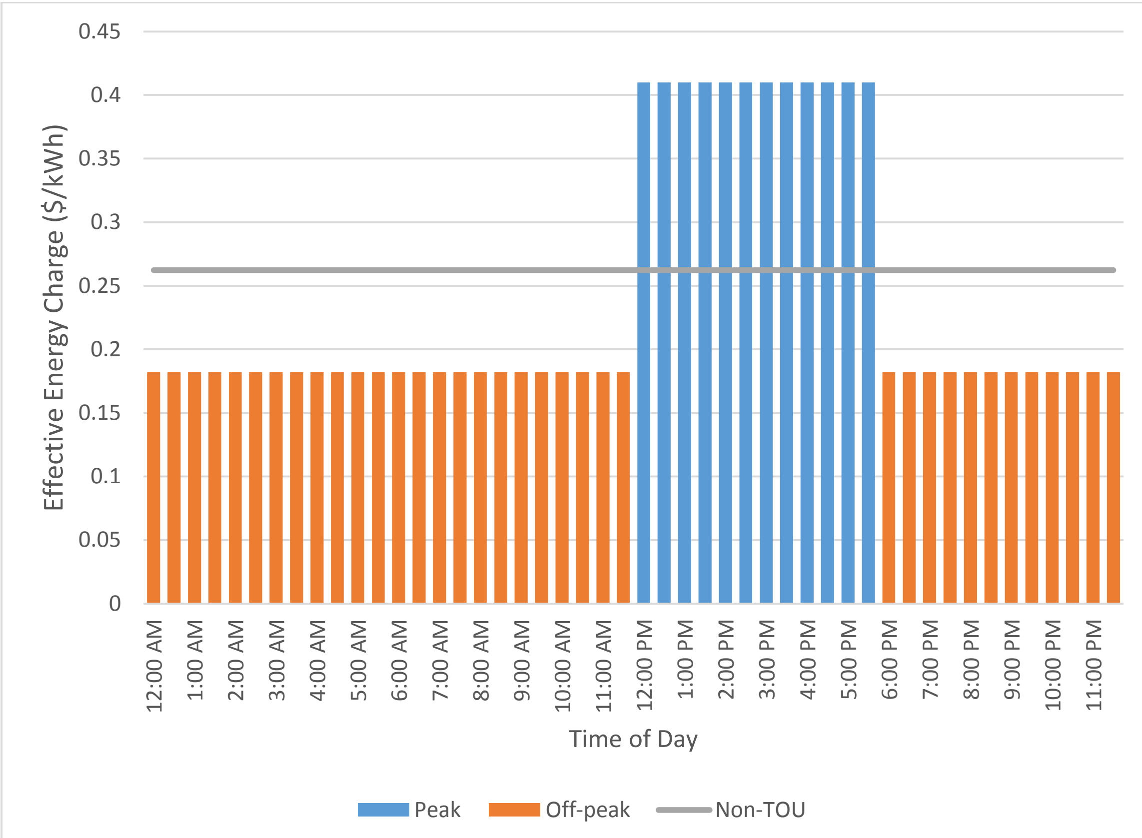
The rate structures of the AG-1 tariff have similar features to the A-10 tariff in that they have demand and energy rates. The TOU version of AG-1 (AG-4) is a two-tier seasonal rate, with a summer peak period from noon to 6:00 pm and winter partial-peak period from 8:30 am to 9:30 pm. Figure 2.3 shows the summer EECs associated with the AG-1 and AG-4 tariffs. One notable difference between the calculations of EECs for AG-4 relative to A-10 described above is the way in which demand charges are "spread" across hours. Because the majority of agricultural customers who transitioned to TOU rates in March 2015 went from the AG-1A to AG-4A rate, which both apply demand charges based on connected load, the demand charge is evenly distributed across all hours. [4] As a result, the EEC for AG-1 is constant throughout the day and is represented in Figure 2.3 by the gray line. The AG-4 peak and off-peak prices are represented by the blue and orange bars, respectively.[5] Differentials between the peak and part-peak EECs for the TOU and non-TOU rates are not as modest as they were for A-1 and A10.

[4] The small share of customers that did not transition to the AG-4A rate in March 2015 went from the AG-1B to AG-4B rate, which apply demand charges based on maximum demand, much like the A-10 rate structure.

[5] Note that because the demand charges are evenly distributed across hours, the peak to off-peak price differentials are solely due to differences in peak to off-peak energy prices.

Specifically, the peak TOU EEC is 56 percent higher than the non-TOU peak EEC and the off-peak TOU EEC is 31 percent lower.

Figure 2.3: Summer TOU and Non-TOU Energy Prices by Time Period – *AG-1/AG-4*



2.2 Transition Process

PG&E has been transitioning small and medium business (SMB) and agricultural customers to mandatory TOU rates since 2012, with cohorts of approximately 225,000 SMB customers transitioned in November 2012, and 144,000 in November 2013. Similarly, cohorts of 17,500 agricultural customer accounts were transitioned in March of 2013. The *ex-pos*t study presented here concerns customers transitioned to TOU rates in November 2014 and March 2015, of which there were 61,000 SMB (November 2014) and 8,300 agricultural customers. Approximately 75,000 customers who lacked necessary metering remained on non-TOU rates, but because of limited data and other unique characteristics, they cannot be used as a control group and are not included in any part of this study.

In order to assess differences in load impacts across customer types, the transitioned customers were categorized according to eight industry types, defined according to their applicable two-digit North American Industry Classification System (NAICS) codes:

1. Agriculture, Mining and Oil and Gas, Construction: 11, 21, 23

2. Manufacturing: 31-33
3. Wholesale, Transport, other Utilities: 22, 42, 48-49
4. Retail stores: 44-45
5. Offices, Hotels, Finance, Services: 51-56, 62, 72
6. Schools: 61
7. Entertainment, Other services and Government: 71, 81, 92
8. Other or unknown.

In addition, PG&E provided information regarding the CAISO Local Capacity Area (LCA) in which the customer resides (if any).[6]

3. Study Methodology

This section describes the methodology used to estimate TOU load impacts for those customer accounts that were newly transitioned to TOU prior to the summer of 2015.

Estimating load impacts for non-event-based rates like TOU requires some form of before and after, or treatment and control group approach, or a combination of the two. In prior years, the availability of customers who had not yet transitioned to a TOU rate provided a pool of comparable control group customers and a difference-in-differences approach was used. In this study, a comparable control group is not available, therefore we are limited to estimating *ex-post* load impacts by comparing load data for treatment (TOU) customers before and after transitioning to TOU rates.

Using the new approach, we are able to control for differences in weather during the pre- and post-treatment periods, but we are unable to account for exogenous changes that a difference-in-differences approach can capture. As a result, our ability to attribute estimated load impacts to TOU rates is substantially limited. To investigate whether exogenous factors are contributing to changes in energy consumption between 2014 and 2015 we also examine load data for previously transitioned TOU customers, specifically those who were included in last year's analysis (*i.e.*, transitioned in November 2013).

The following activities provide an overview of the approach used for this year's evaluation:

- We consider all AG-1 customers and random samples from the A-1 and A-10 customers who were newly transitioned to TOU rates in November 2014 (A-1 and A-10) or March 2015 (AG-1/AG-4);

[6] Local Capacity Area (or LCA) refers to a CAISO-designated load pocket or transmission constrained geographic area for which a utility is required to meet a Local Resource Adequacy capacity requirement. There are currently seven LCAs within PG&E's service area. In addition, PG&E has many accounts that are not located within any specific LCA.

- We perform model validation tests to identify the optimal weather variables to include in each customer group's models for summer and winter seasons;
- We estimate TOU load impacts by hour using fixed-effects panel regressions.
- We compare 2015 load impact estimates for newly transitioned TOU customers to 2015 load impact estimates for customers that were transitioned to TOU in the prior year. This comparison provides context for current-year load impact estimates.

Similar to last year's study (but in contrast to studies before that), we differentiate SMB customers by size group (*i.e.*, under 20 kW versus 20 to 200 kW) rather than tariff (*e.g.*, A-1 versus A-10). This was done to conform to the manner in which PG&E forecasts customer enrollments, and examines and reports its load impacts, which is by customer size.

These activities are described in more detail in the following sub-sections.

3.1 Sample design and selection

The customer accounts that migrated to TOU rates in November 2014 and March 2015 provides a large pool of customers from which to draw a treatment group for use in this study. Given the need to report results for a number of different customer characteristics (*e.g.*, business type, location, and size), we selected a sample of 10,000 small-sized customers, 10,000 medium-sized customers, and used all 7,100 agricultural customers who transitioned in November 2014 and March 2015 and appeared to have suitable data available. After examining interval data for each cohort, the customer groups were further narrowed in order to maximize data quality, leaving 9,417 small customers, 9,919 medium customers, and 6,143 agricultural customers included in the analyses.

3.2 Model Validation

A range of model specifications were tested before arriving at the model used in the *ex-post* load impact analysis. The basic structure of the model is shown in Section 3.3. The tests are conducted using average-customer data by customer group (small, medium, and agricultural) and season (summer and winter).

The model variations are based on different methods of characterizing weather conditions. We tested 22 different combinations of weather variables in the summer and 12 specifications in the winter. The weather variables include: heat index (HI)[7], temperature-humidity index (THI)[8], cooling and heating degree hours (CDH and HDH,

[7] HI = $c_1 + c_2T + c_3R + c_4TR + c_5T^2 + c_6R^2 + c_7T^2R + c_8TR^2 + c_9T^2R^2 + c_{10}T^3 + c_{11}R^3 + c_{12}T^3R + c_{13}TR^3 + c_{14}T^3R^2 + c_{15}T^2R^3 + c_{16}T^3R^3$, where T = ambient dry-bulb temperature in degrees Fahrenheit and R = relative humidity (where 10 percent is expressed as "10"). The values for the various c's may be found here: http://en.wikipedia.org/wiki/Heat_index.

[8] THI = $T - 0.55 \times (1 - HUM) \times (T - 58)$ if T>=58 or THI = T if T<58, where T = ambient dry-bulb temperature in degrees Fahrenheit and HUM = relative humidity (where 10 percent is expressed as "0.10").

respectively)[9], cooling and heating degree days (CDD and HDD, respectively)[10], and the average temperature for the first 17 hours of a given day (MEAN17). These core variables may also be included as current hour, 3- or 24-hour moving averages, or lagged terms, and the degree day and degree hour variables are calculated using either a 60 or 65 degree threshold. A list of the 22 summer and 12 winter combinations of these variables that we tested is provided in Table 3.1. Selected weather specifications are highlighted. [11]

[9] Cooling degree hours (CDH) was defined as MAX[0, Temperature – Threshold], where Temperature is the hourly temperature in degrees Fahrenheit and Threshold is either 60 or 65 degrees Fahrenheit. Customer-specific CDH values are calculated using data from the most appropriate weather station.

[10] Cooling degree days (CDD) are defined as MAX[0, (Max Temp + Min Temp) / 2 – Threshold], 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.

[11] Model 21 was selected for small and medium customers in the summer season. Model 3 was selected for agricultural customers in the summer season. Model 11 was selected for small and medium customers in the winter season.

Table 3.1: Weather Variables Included in Specification Search

Model Number	Summer	Winter
1	THI	CDH60, HDH60
2	HI	CDH65, HDH65
3	CDH60	CDH60, CDH60_24MA, HDH60, HDH60_24MA
4	CDH65	CDH65, CDH65_24MA, HDH65, HDH65_24MA
5	CDH60_3MA	CDH60, CDD60, HDH60, HDD60
6	CDH65_3MA	CDH65, CDD65, HDH65, HDD65
7	THI, THI_24MA	CDH60, LagCDD60, HDH60, LagHDD60
8	HI, HI_24MA	CDH65, LagCDD65, HDH65, LagHDD65
9	CDH60, CDH60_24MA	MEAN17
10	CDH65, CDH65_24MA	MEAN17, CDH60, HDH60
11	CDH60_3MA, CDH60_24MA	MEAN17, CDH65, HDH65
12	CDH65_3MA, CDH65_24MA	CDD60, HDD60
13	THI, LagCDD60	
14	HI, LagCDD60	
15	CDH60, LagCDD60	
16	CDH65, LagCDD60	
17	CDH60_3MA, LagCDD60	
18	CDH65_3MA, LagCDD60	
19	MEAN17	
20	CDH60, MEAN17	
21	CDH65, MEAN17	
22	CDD60, HDD60	

Additional details and results of the model specification search can be found in Appendix A.

3.3 Estimation of demand and energy impacts

We conducted a range of analyses to estimate TOU demand and energy impacts, as follows:

- We begin by considering *simple statistical and graphical comparisons* of usage levels and weather conditions in the periods before and after customers transitioned to TOU rates. These comparisons provide a preliminary indication of changes in weather sensitivity or electricity consumption behavior that a formal regression model may attribute to TOU rates.
- We conduct formal regression analyses in order to account for factors such as weather conditions and to produce hourly estimates of TOU load impacts. An

appropriate regression approach for this type of time-series and cross-sectional data is *fixed-effects* regression. This approach effectively includes customer-specific indicator variables to control for factors unique to each customer, along with time-series indicator variables to distinguish day of week, month, and whether the observation is in the pre- or post-TOU period. Weather variables appropriate for each season and customer class are also included. Each hour is modeled separately and the estimated coefficient on the variable for the post-TOU period represents an estimate of the effect of participation in the TOU rate.

- A second regression approach is used to develop all of the scenarios required to meet the Protocols (*e.g.*, typical weekday and system peak day by month). This method is an *aggregate* version of the above approach, which averages usage observations across customers in various sub-groups. The dependent variable is the natural log of average load for the customer group in question (*e.g*., small TOU customers in the Greater Bay Area) and the explanatory variables control for weather, hour-of-day, day-of-week, and month-of-year effects. This approach produces hourly estimates of TOU load impacts in percentage terms, facilitating the estimation of TOU load impacts on days with relatively high (or low) load levels, typically associated with higher (or more mild) temperatures.

In all of the above analyses, TOU load impacts are estimated for summer and winter seasons, by hour, and in accordance with the parameters specified in the CPUC Load Impact Protocols (*e.g.*, hourly impacts for the average weekday, and hourly impacts for the monthly system peak day). In addition, these estimates are combined to produce estimates of the effect of TOU rates on overall energy usage.

The second bullet point above describes the model used to estimate our primary results (the hourly load impacts for SMB and agricultural customers), while the third bullet point above describes the model used to develop the full range of *ex-post* and *ex-ante* scenarios required by the Protocols.

Separate models are estimated for the summer (May through September) and winter (January through April for small and medium-sized customers, winter cannot be estimated for agricultural customers) seasons and for weekdays and weekends within each of those seasons.[12] The regression equation is defined as follows:

$$Q_{t,c}^{h} = a + b_{Post}^{h} \times Post_{t} + b_{Weather}^{h} \times Weather_{t,c}^{h} + \sum_{i} (b_{DTYPEi}^{h} \times DTYPE_{i,t})$$

$$+ \sum_{i} (b_{i}^{MONTH\_YR} \times MONTH\_YR_{i,t}) + u_{c} + e_{t,c}$$

[12] October 2015 data were not available when the study commenced. For small and medium-sized customers, we do not use October through December 2014 data because we do not have corresponding 2015 data and because we want to avoid incorporating data during the TOU transition period. For agricultural customers, we do not use data from January through March of 2014 or 2015 to avoid incorporating data during the agricultural TOU transition period.

Table 3.2: Descriptions of Terms included in the Regression Equation

Variable Name / Term	Variable / Term Description
$Q^h_{t,c}$	the demand in hour *h* on date *t* for customer *c*
a and the *b* parameters	the estimated parameters
$Post_t$	a dummy variable for the post-transition time period
$Weather^h_{t,c}$	Weather variables may include one or more of the following: • *CDH* – cooling degree hours (60 or 65 degree threshold) in hour *h* on date *t* for customer *c* • *HDH* – heating degree hours (65 degree threshold) in hour *h* on date *t* for customer *c* • Mean17 – average temperature from midnight to 5pm on date *t* for customer *c*
$DTYPE_{i,t}$	a series of dummy variables for each day of the week
$MONTH\_YR_{i,t}$	a series of dummy variables for each month/year
u_c	the customer fixed effect.
$e_{t,c}$	the error term.

The *Post* variable is equal to one for all customers following the TOU transition (2015 in this case) and zero before the transition, and provides the estimate of TOU load response during the hour in question. The weather variables account for each customer's weather conditions during each hour/day.[13]

Separate models are estimated for the small, medium, and agricultural business customer groups; for weekends and weekdays; for summer and winter seasons (winter is not estimated for agricultural customers); and for each hour of the day (240 distinct models). Each model includes all of the treatment customers within a given customer class.

Because of the large number of models (and numbers of customers within each model), we developed similar models using aggregated loads for the various required sub-groups (*e.g.*, by LCA) where the dependent variable is the natural log of usage producing estimates of TOU load impacts in percentage terms. The weather variables are load-weighted averages across the included customers.

3.4 Comparison to Previously Transitioned TOU Customers

Because the program year 2015 (PY 2015) analysis does not have the advantage of a comparable control group, we cannot conclusively attribute estimated load impacts to the introduction of TOU rates. It is likely that exogenous factors also affected usage behavior for newly transitioned TOU customers from 2014 to 2015. Weather is often a

[13] CDH60 = MAX(Average of the Max and Min Daily Temperatures in degrees Fahrenheit – 60, 0)
CDH65 = MAX(Average of the Max and Min Daily Temperatures in degrees Fahrenheit – 65, 0)
HDH65 = MAX(65 – Average of the Max and Min Daily Temperatures in degrees Fahrenheit, 0)

primary driver of electricity consumption, but conditions were similar across years and weather is accounted for in our models. Other possible factors include economic conditions, firmographic changes, and non-temperature related weather conditions (*e.g.*, drought).

In order to detect the presence of exogenous factors, we leveraged data from last year's analysis (PY 2014) by obtaining updated interval data for customers that transitioned to TOU rates in November 2013 and assessing changes in their consumption patterns from 2014 to 2015. Unfortunately, again, we do not have the advantage of a control group (most or all of the previous control customers transitioned to TOU in November 2014), but the behavior of PY 2014's treatment customers during year two on the TOU rate (2015) provides context for load impacts estimated for newly transitioned TOU customers.

Further, to provide another basis for comparison, we replicated the current program year's methodology (treatment customers only, excluding the control group) using the previous program year's data and model.[14] The difference-in-differences approach presented in the PY 2014 report produced summer peak period percentage load impacts of 2.1 and 2.4 percent for small and medium businesses, respectively. We believe this method produces the best possible estimate of TOU load impacts for that year. Performing the same analysis without a control group may provide insight regarding bias or inaccuracy in the simple panel model approach employed in the PY 2015 analysis. For example, if excluding the control group from last year's analysis of small businesses produces load impact estimates of 3 percent, rather than the aforementioned 2.1 percent, then we may conclude that the panel model overestimates load response and make adjustments to this year's estimates accordingly.[15]

Unfortunately, neither of these approaches yielded conclusive evidence of exogenous factors or bias in the current year's study, but several patterns did emerge that may inform our interpretation of results going forward.

First, excluding control customers from PY 2014's analysis did not consistently increase or decrease the estimated load impacts across size groups or TOU pricing periods. That is, we cannot deduce from this exercise that the PY 2015 methodology is likely to underestimate or overestimate TOU load response. [16] Table 3.3 shows percent TOU load impact estimates by TOU pricing period for small and medium businesses using both approaches applied to the PY 2014 data. For small businesses, excluding the control

[14] The PY 2014 model was used in this exercise in order to isolate the effect of excluding the control group.

[15] This approach would not provide us information about the nature of exogenous effects in the PY 2015 study, as they may differ from the PY 2014 exogenous factors.

[16] Even if this method did result in consistently increased or decreased impacts, in order to conclude that the same bias is affecting the PY 2015 results, we would have to assume that whatever exogenous affects are driving the trend from 2013 to 2014 also persist from 2014 to 2015.

group produces smaller estimated load reductions (and in some cases load increases) for some TOU pricing periods and larger load reductions in other periods. For medium businesses, all TOU pricing periods have estimated load increases when control customers are excluded, as opposed to load decreases with the control group. While this exercise does not provide evidence that excluding the control group introduces specific positive or negative bias in the estimates, it does suggest that results from a panel model of this sort without a control group should be interpreted with caution, as they are not robust to methodology.

Table 3.3: PY 2014 TOU Load Impact Estimates, With and Without a Control Group

TOU Pricing Period			% TOU Load Impact:			
			Small		Medium	
			PY 2014 Report	Excluding Controls	PY 2014 Report	Excluding Controls
Summer	Weekdays	Peak	-2.1%	-0.7%	-2.4%	5.2%
		Part-Peak	-2.5%	-0.1%	-2.3%	4.5%
		Off-Peak	-2.1%	2.5%	-2.6%	5.3%
	Weekends & Holidays	Off-Peak	-1.9%	-1.9%	-2.4%	0.5%
Winter	Weekdays	Part-Peak	-1.9%	-2.9%	-3.5%	5.7%
		Off-Peak	-1.6%	-1.3%	-3.7%	5.1%
	Weekends & Holidays	Off-Peak	-1.6%	-5.4%	-3.7%	1.6%

Second, extending the PY 2014 analysis into 2015 produces estimates of TOU load response for customers during their second year on TOU rates.[17] Estimated load reductions for these customers could be evidence of widespread reduced usage in 2015 due to exogenous factors, or it could reflect increased TOU responsiveness after additional experience on the TOU rate. Table 3.4 summarizes 2015 estimated load impacts by season and TOU pricing period for customers on their first year (PY 2015 customers, presented in Sections 4 and 5) and second year (PY 2014 customers) of TOU rates. During the second year on TOU rates, PY 2014 small business customers reduced usage in all periods except off-peak weekdays. Medium businesses reduced usage during the summer and increased usage during the winter season. Usage reductions in the "extended" scenarios could reflect increased TOU response or the effect of exogenous factors on comparisons of usage levels across years.

Table 3.4: 2015 TOU Load Impact Estimates, PY 2015 versus Extension of PY 2014

TOU Pricing Period	2015 % TOU Load Impact:

[17] The extended model for PY 2014 customers includes data from 2014 and 2015, so load impact estimates for 2015 are incremental to the TOU load response customers exhibited during their first year on TOU rates (2014). That is, estimates of zero percent imply persistence of year one TOU load response. Again, models used for this exercise do not include a control group.

			Small		Medium	
			PY 2015	PY 2014 Extended w/o Controls	PY 2015	PY 2014 Extended w/o Controls
Summer	Weekdays	Peak	-2.9%	-1.4%	-2.1%	-1.8%
		Part-Peak	-2.6%	-0.5%	-1.8%	-1.6%
		Off-Peak	-2.1%	0.4%	-1.3%	-1.3%
	Weekends & Holidays	Off-Peak	-2.4%	-0.2%	-1.5%	-1.6%
Winter	Weekdays	Part-Peak	-2.4%	-0.7%	-0.5%	0.2%
		Off-Peak	-2.4%	0.3%	-0.3%	0.7%
	Weekends & Holidays	Off-Peak	-3.4%	-1.0%	-0.9%	0.1%

Ultimately, these exercises produce inconclusive results and inferences from them would be speculative, therefore we do not use them to adjust the current program year's estimated TOU load impacts. However, these results should serve as cautionary reminders that findings presented in Sections 4 through 6 may not be robust to methodology and estimated TOU load impacts may in fact be due, in part or in whole, to exogenous factors.

4. Small Business Customer Findings

In order to analyze the effect of TOU rates on small (maximum demands below 20 kW) business customer usage, we first compile a set of eligible treatment customers with sufficient pre- and post-treatment interval data (approximately 33,000 out of 38,000 small-sized November 2014 TOU transitioners). We then select a random sample of 10,000 accounts, and, after applying screens to ensure quality of the data, we are left with 9,417 treatment customers. Table 4.1 summarizes the customer counts.

Table 4.1: Numbers of Small Business Treatment Customers

	# Treatment Customers
November 2014 TOU Transitioners	38,091
Eligible for Analysis	33,363
Sampled for Analysis	10,000
Used in Analysis	9,417

4.1 Graphical and Statistical Comparisons of Load Levels

As described in Section 3.1, we conduct several analyses to estimate TOU demand and energy impacts. The first analysis is a simple statistical and graphical comparison of average treatment customer loads and weather conditions during pre-TOU and post-TOU periods.

Figures 4.1 and 4.2 show average weekday load profiles for small businesses before (2014) and after (2015) transitioning to TOU rates during summer and winter periods, respectively. Average temperature profiles for each season and year are also displayed and measured on the secondary axis. In both seasons, there is very little difference in average temperatures from 2014 to 2015, but there is a more pronounced difference in average load levels, particularly in afternoon hours. Specifically, in summer 2015, usage levels are equal to or lower than summer 2014 levels in all hours and lower still during peak hours. Load levels are lower in all hours during the winter 2015 season, and temperatures are slightly higher.

Figure 4.1: Average Loads and Temperatures for Small Business Customers - Summer Weekdays

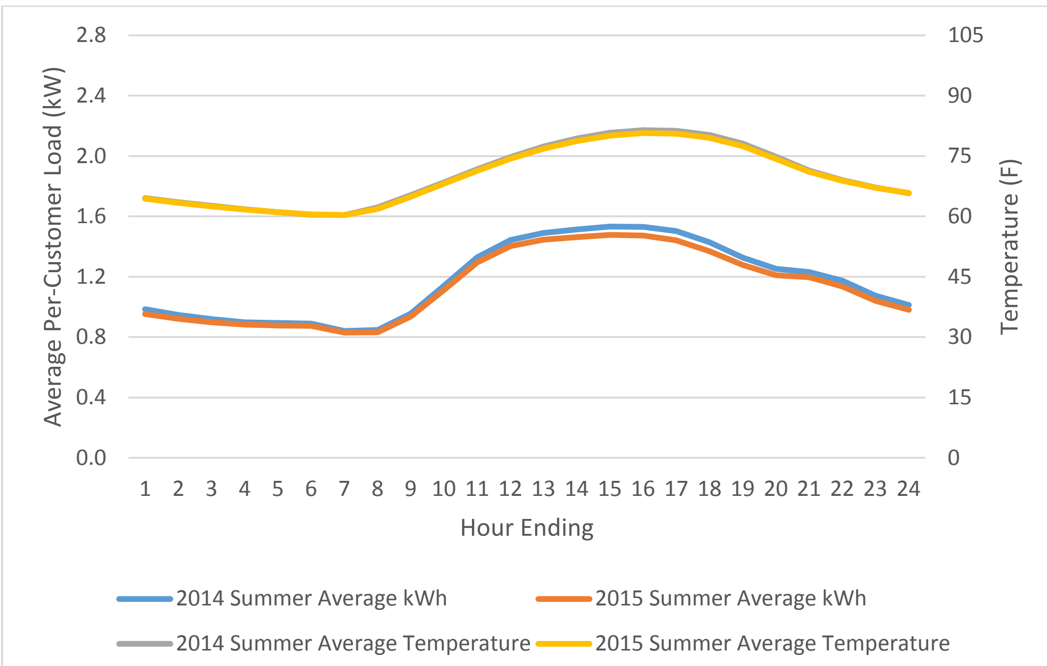


Figure 4.2: Average Loads and Temperatures for Small Business Customers - Winter Weekdays

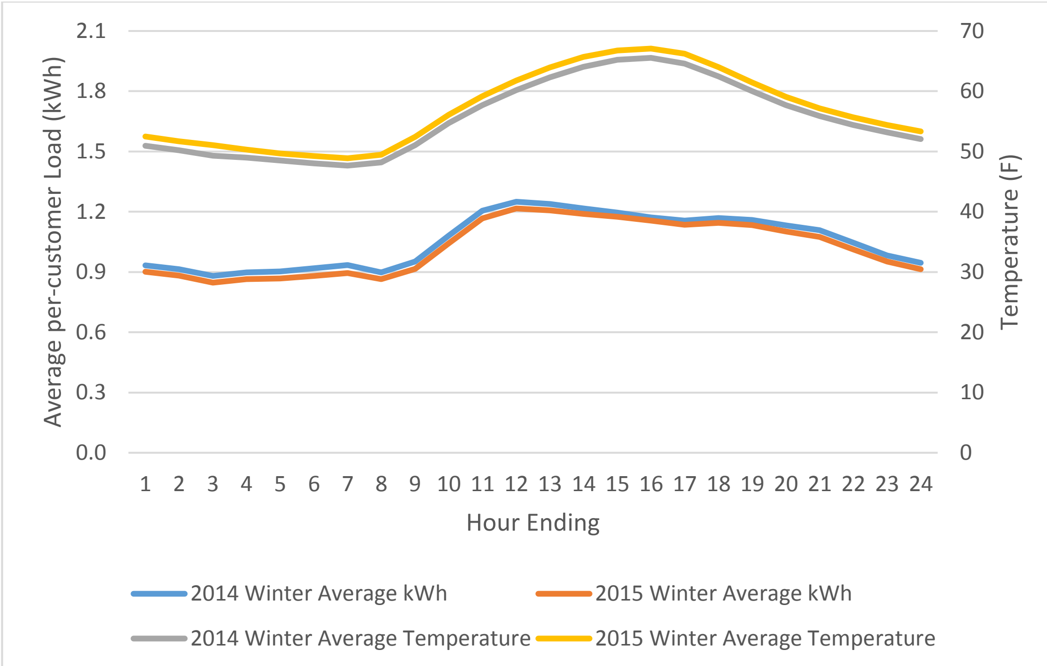


Table 4.2 summarizes seasonal percent differences in average load levels and temperatures from 2014 to 2015 in terms of TOU pricing period (peak, partial-peak, and off-peak).

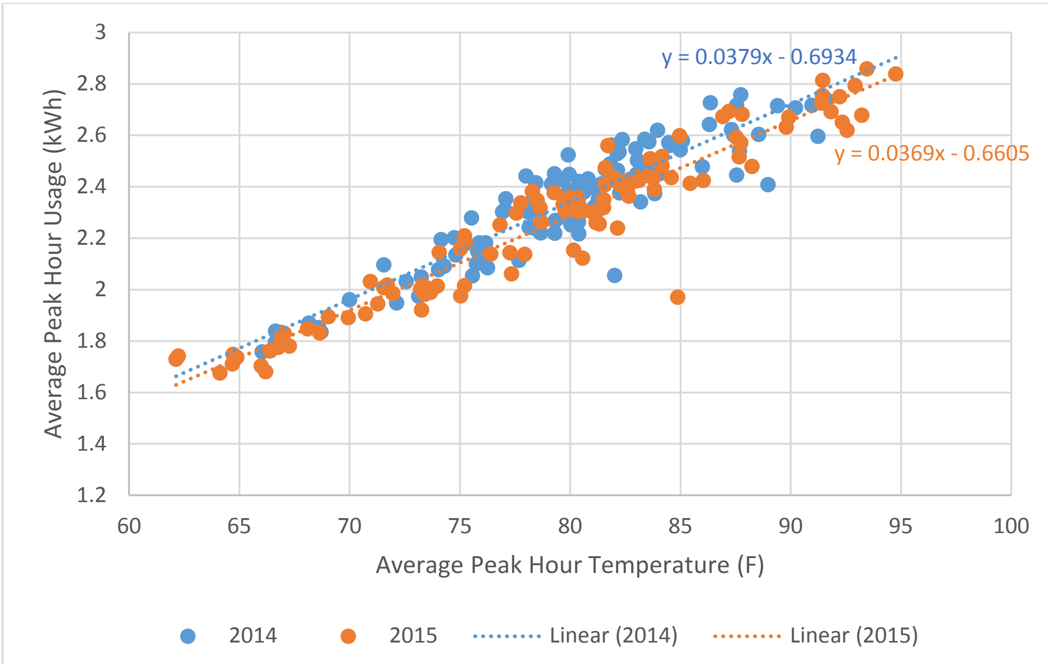
Table 4.2: Small Business Percent Change in Average Load Levels and Temperatures by Pricing Period

TOU Pricing Period			YoY % Change in Average:	
			Load	**Temperatures**
Summer	Weekdays	Peak	-3.6%	-0.8%
		Part-Peak	-2.9%	-0.6%
		Off-Peak	-2.3%	-0.1%
	Weekends & Holidays	Off-Peak	-2.8%	-0.7%
Winter	Weekdays	Part-Peak	-2.6%	2.5%
		Off-Peak	-3.7%	2.7%
	Weekends & Holidays	Off-Peak	-3.2%	1.0%

Figure 4.3 shows average peak-hour usage plotted against temperatures in the summers of 2014 and 2015. Each data point represents one day. Linear trend lines and corresponding equations are also provided. The figure confirms the temperature and load level differences shown in Figure 4.1 and also illustrates that there was little change in weather sensitivity across years. That is, the slope of the trend lines are very

similar for 2014 and 2015. In 2014, on average, a ten degree increase in temperature corresponded to an additional 0.38 kWh usage per peak-hour, whereas a similar increase in temperature during 2015 corresponded to an additional 0.37 kWh usage per hour. On average, for any given temperature, peak-hour usage is 0.03 kWh lower in 2015 relative to 2014.

Figure 4.3: Average Peak Loads and Temperatures for Small Business Customers, Summer Weekdays



4.2 Estimation Results

As discussed in Section 3.1, the limitation of the simple graphical and statistical comparisons presented in Section 4.1 is that they average across all available days and customers, and thus do not formally account for the effects of factors such as weather conditions or idiosyncratic customer variations. To account for these nuances, we employ a fixed-effects regression model and obtain an estimate of load impacts on an hourly basis. The estimated hourly coefficients can be added to observed loads for TOU customers in the post-TOU period, providing an estimate of the treatment customer reference load, or the load that would have occurred absent TOU rates. Dividing that coefficient by the reference load provides an estimate of the TOU load impact expressed in percentage terms.

Table 4.3 contains estimated hourly reference loads, actual average observed loads, and estimated percent load impacts for summer weekdays and weekends based on fixed-effects regression models. Each of the estimated coefficients used to calculate summer percent load impacts is statistically significant at the 0.05 (95 percent confidence) level.

Table 4.4 displays similar results for the winter period. All estimated coefficients used to calculate winter percent load impacts are also statistically significant.

Table 4.3: Small Business Estimated Load Impacts from Hourly Regression – Summer

	Weekday			Weekend		
Hour	**Reference kWh**	**Observed kWh**	**% Load Impact**	**Reference kWh**	**Observed kWh**	**% Load Impact**
1	0.98	0.95	-2.7%	0.97	0.95	-2.1%
2	0.94	0.92	-2.2%	0.94	0.92	-1.7%
3	0.92	0.90	-1.8%	0.91	0.90	-1.4%
4	0.90	0.89	-1.4%	0.89	0.88	-0.9%
5	0.91	0.90	-1.6%	0.89	0.88	-0.9%
6	0.95	0.93	-1.8%	0.88	0.87	-0.9%
7	1.00	0.98	-1.3%	0.83	0.83	-0.4%
8	1.19	1.17	-2.0%	0.84	0.83	-0.9%
9	1.55	1.51	-2.2%	0.95	0.94	-1.3%
10	1.85	1.82	-1.8%	1.14	1.11	-2.2%
11	2.11	2.06	-2.1%	1.33	1.29	-2.7%
12	2.25	2.20	-2.2%	1.44	1.40	-2.8%
13	2.31	2.25	-2.6%	1.49	1.44	-3.0%
14	2.40	2.33	-2.9%	1.51	1.46	-3.2%
15	2.47	2.39	-2.9%	1.53	1.48	-3.3%
16	2.45	2.38	-2.9%	1.53	1.47	-3.5%
17	2.33	2.26	-3.1%	1.50	1.44	-3.9%
18	1.98	1.92	-3.2%	1.43	1.37	-3.9%
19	1.67	1.62	-2.9%	1.32	1.28	-3.5%
20	1.49	1.45	-3.2%	1.25	1.21	-3.1%
21	1.39	1.35	-2.9%	1.23	1.20	-2.5%
22	1.25	1.21	-3.2%	1.17	1.14	-3.0%
23	1.11	1.08	-2.9%	1.07	1.04	-2.8%
24	1.03	1.00	-2.9%	1.01	0.98	-2.7%
Averages						
Peak	2.32	2.26	-2.9%			
Part Peak	1.70	1.65	-2.6%			
Off Peak	0.99	0.97	-2.1%	1.17	1.14	-2.4%

Table 4.4: Small Business Estimated Load Impacts from Hourly Regression – Winter

	Weekday			Weekend		
Hour	Reference kWh	Observed kWh	% Load Impact	Reference kWh	Observed kWh	% Load Impact
1	0.92	0.89	-2.5%	0.94	0.90	-3.8%
2	0.90	0.88	-2.5%	0.92	0.88	-3.9%
3	0.89	0.87	-2.6%	0.86	0.85	-1.6%
4	0.89	0.87	-2.6%	0.90	0.86	-4.1%
5	0.91	0.89	-2.4%	0.91	0.87	-4.2%
6	0.97	0.95	-2.0%	0.92	0.88	-4.3%
7	1.08	1.06	-1.9%	0.93	0.90	-4.2%
8	1.24	1.21	-2.3%	0.89	0.86	-3.3%
9	1.54	1.50	-2.5%	0.95	0.92	-3.2%
10	1.77	1.72	-2.5%	1.08	1.04	-3.3%
11	1.91	1.86	-2.4%	1.21	1.17	-3.3%
12	1.94	1.89	-2.3%	1.25	1.22	-3.0%
13	1.90	1.85	-2.2%	1.25	1.21	-3.2%
14	1.90	1.85	-2.3%	1.23	1.19	-3.1%
15	1.89	1.85	-2.3%	1.21	1.17	-3.0%
16	1.85	1.82	-2.0%	1.19	1.15	-2.8%
17	1.76	1.73	-1.7%	1.17	1.14	-3.3%
18	1.58	1.55	-2.1%	1.19	1.15	-3.4%
19	1.43	1.41	-1.9%	1.17	1.13	-3.2%
20	1.34	1.30	-2.7%	1.14	1.10	-3.3%
21	1.24	1.20	-3.2%	1.11	1.07	-3.5%
22	1.11	1.08	-3.4%	1.05	1.01	-3.6%
23	1.01	0.98	-2.8%	0.99	0.95	-3.7%
24	0.95	0.93	-2.7%	0.95	0.91	-4.0%
Averages						
Peak						
Part Peak	1.65	1.62	-2.4%			
Off Peak	0.98	0.95	-2.4%	1.06	1.02	-3.4%

The average values at the bottom of Tables 4.3 and 4.4 represent average hourly load impacts for each TOU pricing period, and they show that TOU rates lead to energy reductions in all periods in both the summer and winter seasons. The largest reduction, 2.9 percent, occurs during summer peak hours, with slightly smaller reductions during summer part peak hours of 2.6 percent. Both of these reductions are larger than those calculated for off-peak summer hours (2.1 percent on weekdays and 2.4 percent on weekends).

The load impacts are not entirely consistent with our expectations for TOU demand response. That is, we would expect customers to reduce usage in higher-priced periods (peak hours), but increase usage (or not change usage) in the lowest-priced periods (off-peak hours. Instead, we estimate usage reductions in all hours. These estimates look more like conservation in response to increased awareness of energy use than TOU demand response to changing price signals.[18] This is consistent with the findings from PY 2014, which had the advantage of using a control group.

The average values at the bottom of Tables 4.3 and 4.4 can be compared to those from the simple calculations presented in Table 4.2. Percent load impacts are smaller in both summer and winter seasons using fixed-effects regression, but the pattern across peak, part-peak, and off-peak periods is similar. That is, all periods experience post-TOU load reductions, and in the summer season peak hours have the largest percent load reductions. Table 4.5 summarizes the load impacts calculated or estimated by both methods in all TOU pricing periods.

Table 4.5: Small Business Comparison of Estimated and Calculated Load Impacts, Two Analysis Methods

TOU Pricing Period			% TOU Load Impact:	
			Simple Differences	Fixed-Effects Regression
Summer	Weekdays	Peak	-3.6%	-2.9%
		Part-Peak	-2.9%	-2.6%
		Off-Peak	-2.3%	-2.1%
	Weekends & Holidays	Off-Peak	-2.8%	-2.4%
Winter	Weekdays	Part-Peak	-2.6%	-2.4%
		Off-Peak	-3.7%	-2.4%
	Weekends & Holidays	Off-Peak	-3.2%	-3.4%

Load impact estimates presented thus far are derived from models that include all sampled small businesses that transitioned to TOU rates in November 2014. We perform similar analyses on subsets of customers organized by either local capacity area (LCA) or industry group. The primary difference in these models, aside from the subsets of customers included, is that we first *aggregate* the customer-level data by calculating average usage observations across customers in the sub-groups. This approach facilitates running regressions for many sub-groups and allows us to more easily investigate the effect of weather on TOU load impacts by interacting various weather variables with the TOU treatment indicator variable.

Unfortunately, interacting weather variables with the TOU treatment indicator introduced too much variability into load impact estimates and often produced inconsistent and unrealistic results. Most of the estimated coefficients on weather interactions were not statistically significant, and the implied relationship was not consistently positive or negative, either across sub-groups or within sub-group across hours. The ambiguous effect of weather on TOU response is highlighted in Figure 4.3,

[18] However, the fact that peak usage reductions are higher than part-peak, and both of those reductions are higher than off-peak usage reductions is somewhat consistent with TOU demand response.

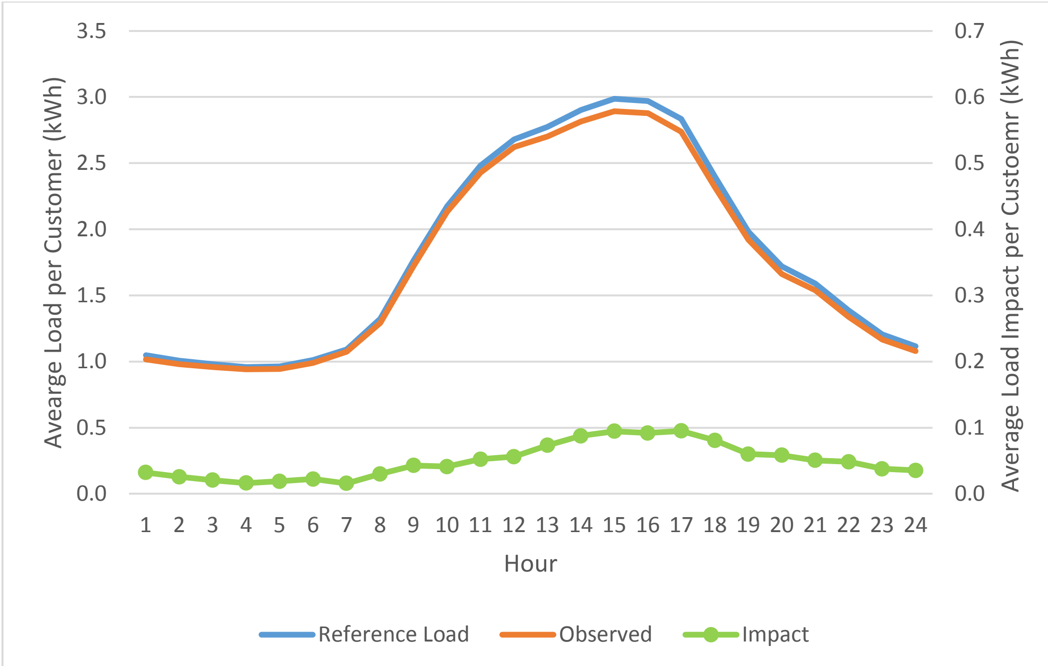
where the slopes of the trend lines are similar in both years, suggesting that the introduction of TOU rates did not affect weather sensitivity.

As a result, when constructing estimated load impacts that correspond to monthly average weekdays and system peak days, in accordance with the CPUC Load Impact Protocols, we opted to estimate the load impacts in percentage terms.[19] That is, the dependent variable in these models is the natural log of average hourly load for the customer group in question (*e.g.,* small TOU customers in the Greater Bay Area) and the explanatory variables control for weather, hour-of-day, day-of-week, and month-of-year effects. This approach produces dynamic levels of TOU response that are related to load levels on different day types, but not explicitly related to temperatures.

Figure 4.4 illustrates average estimated reference loads, actual observed loads, and estimated load impacts on the 2015 August system peak day for all small business customers. The usage levels displayed in the graph are similar to those presented in Table 4.3, but higher reflecting different weather conditions on the August system peak day. The average percent load impact during the peak period is -3.1 percent, which is again similar to but slightly higher than those found in the fixed-effects analysis for peak periods during all summer weekdays. In this case, the difference in percentage terms is not due to weather conditions, but is instead due to the difference in methodology as described above (using the natural log of kWh in place of the level of kWh as the dependent variable). The same pattern that we found previously for part-peak and off-peak periods holds as well, with average part-peak load impacts of -2.6 percent and off-peak load impacts of -2.4 percent.

[19] We cap hourly percent load impact estimates at +/- 10 percent, as it is likely that any estimated impacts larger than 10 percent are due to exogenous factors rather than the introduction of TOU rates. This constraint is only met for a small share of hours in sub-groups with limited numbers of customers in the small business and agricultural business categories.

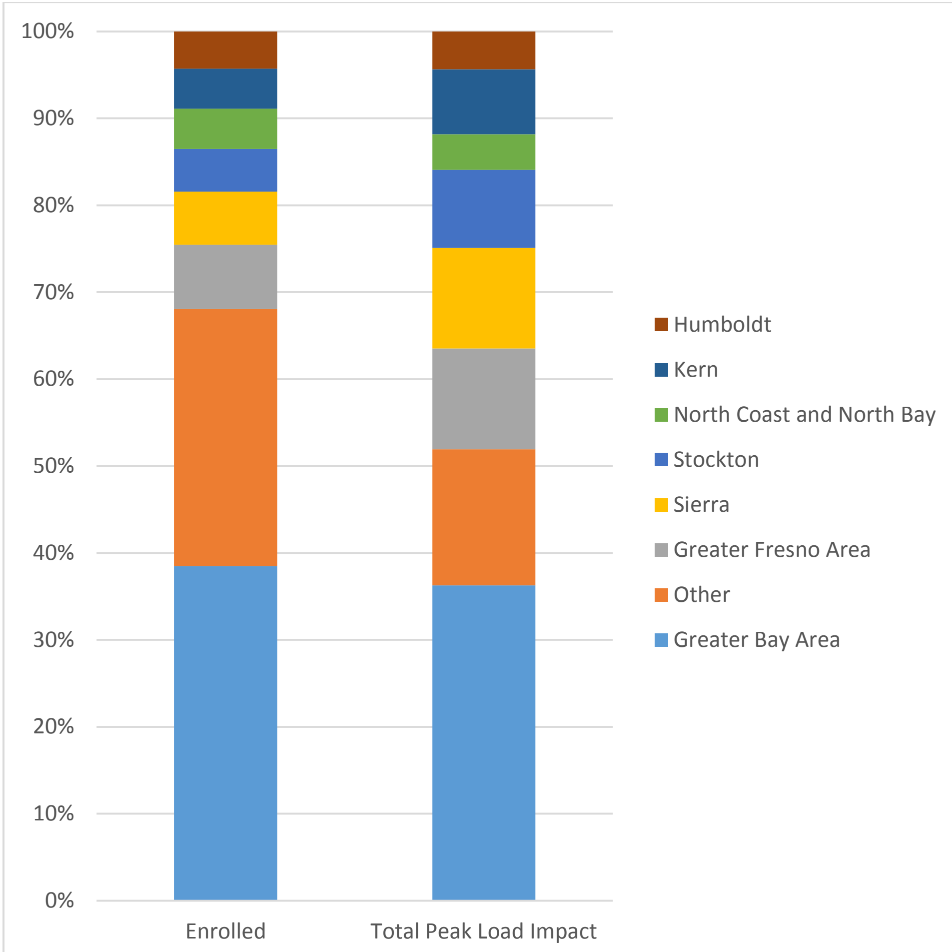
Figure 4.4: August System Peak Reference Loads and Load Impacts for All Small Businesses (Average Per Customer kWh)



Figures 4.5 and 4.6 illustrate the distribution of total load impacts across LCAs and industry groups, respectively. The left bar represents the distribution of customer enrollments, and the underlying values for the right bar are total load impacts during the peak TOU pricing period (noon to 6 p.m.) under weather conditions that occurred during the August 2015 system peak day.

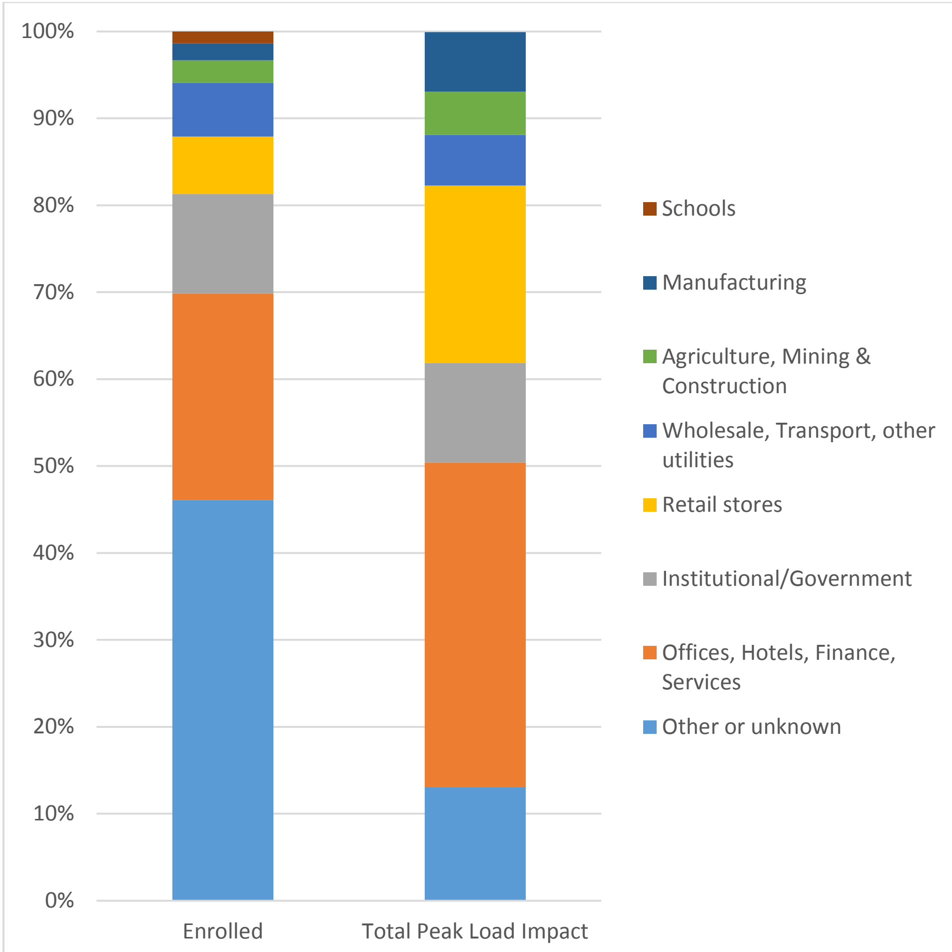
In Figure 4.5, the largest share of total load impacts and customers, roughly 40 percent, comes from the Greater Bay Area. The “Other” LCA group contributes the next largest share of load reductions, 16 percent, but makes up 30 percent of the population. The disparity between load impacts and customers in the “Other” LCA group is made up for by the remaining LCAs, with each (except for North Coast) contributing more than their customer share to total load reductions.

Figure 4.5: Small Business August System Peak Distribution of Load Impacts by LCA



In Figure 4.6, the “Other or Unknown” industry group makes up almost half of the enrolled customers, but only accounts for 13 percent of the total load impacts. The next largest industry group is “Offices, Hotels, Finance, Services”, which makes up a quarter of the enrolled customers and contributes 37 percent of the load impacts. The remaining industries contribute shares of load impacts that are similar to their shares of the population. One exception is “Retail stores” which only represents seven percent of the population and contributes 20 percent of the load impact. The “Schools” sector experiences modest estimated load increases (0.1 percent), which is a negative contribution to load reductions and is not presented in the graph.

Figure 4.6: Small Business August System Peak Distribution Load Impacts by Industry



5. Medium Business Customer Findings

The effect of TOU rates on medium business customer (with maximum demands between 20 to 200 kW) energy usage is analyzed in a similar fashion as that described in Section 4 for small business customers. We first compile a set of eligible treatment customers with sufficient pre- and post-treatment interval data (approximately 21,000 out of 23,000 medium-sized November 2014 TOU transitioners). We then select a random sample of 10,000 accounts, and, after applying screens to ensure quality of the data, we are left with 9,919 treatment customers. Table 5.1 summarizes the customer counts.

Table 5.1: Numbers of Medium Business Treatment Customers

	# Treatment Customers
November 2014 TOU Transitioners	23,393
Eligible for Analysis	21,423
Sampled for Analysis	10,000
Used in Analysis	9,919

5.1 Graphical and Statistical Comparisons of Load Levels

As described in Section 3.1, we conduct several analyses to estimate TOU demand and energy impacts. The first analysis is a simple statistical and graphical comparison of average treatment customer loads and weather conditions during pre-TOU and post-TOU periods.

Figures 5.1 and 5.2 show average weekday load profiles for medium businesses before (2014) and after (2015) transitioning to TOU rates during summer and winter periods, respectively. Average temperature profiles for each season and year are also displayed and measured on the secondary axis. In the summer seasons, there is very little difference in average temperatures from 2014 to 2015, but there is a modest difference in average load levels, specifically, 2015 usage levels are lower than 2014 levels in all hours and lower still during peak hours. Winter temperatures are higher in 2015 than 2014, but winter load levels are only marginally higher from 10:00 a.m. to 8:00 p.m. and lower in morning and late evening hours.

Figure 5.1: Average Loads and Temperatures for Medium Business Customers - Summer Weekdays

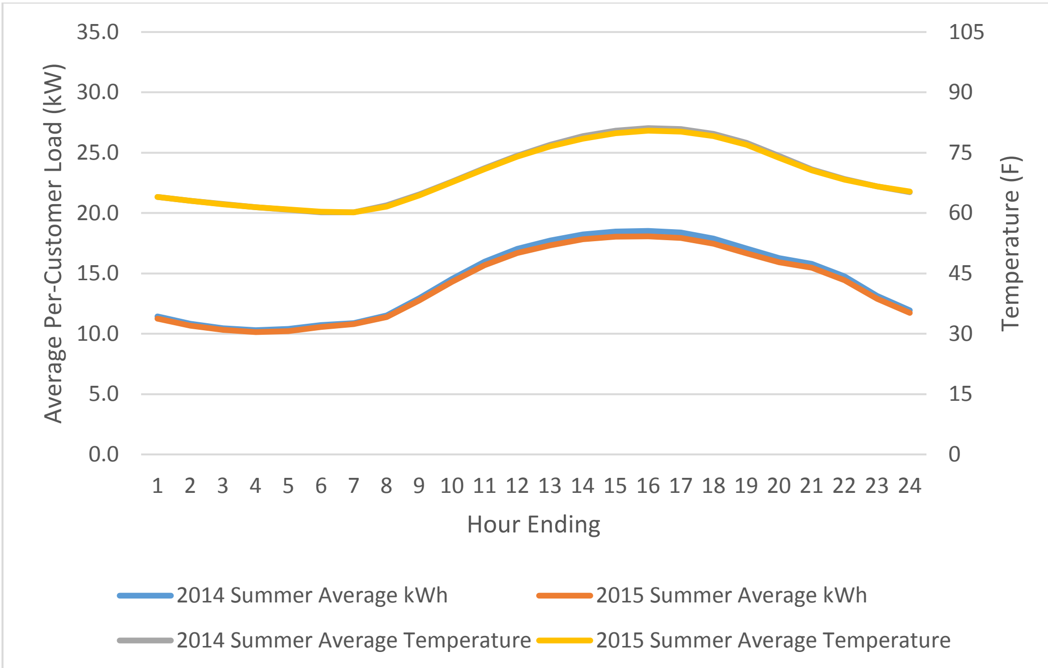


Figure 5.2: Average Loads and Temperatures for Medium Business Customers - Winter Weekdays

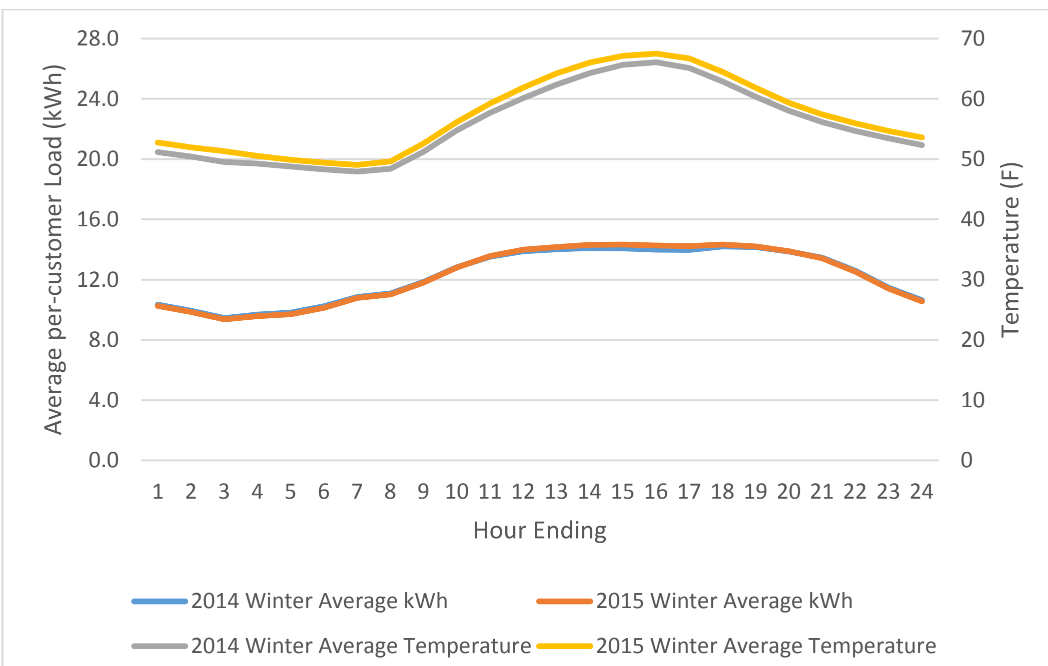


Table 5.2 summarizes seasonal percent differences in average load levels and temperatures from 2014 to 2015 in terms of TOU pricing period (peak, partial-peak, and

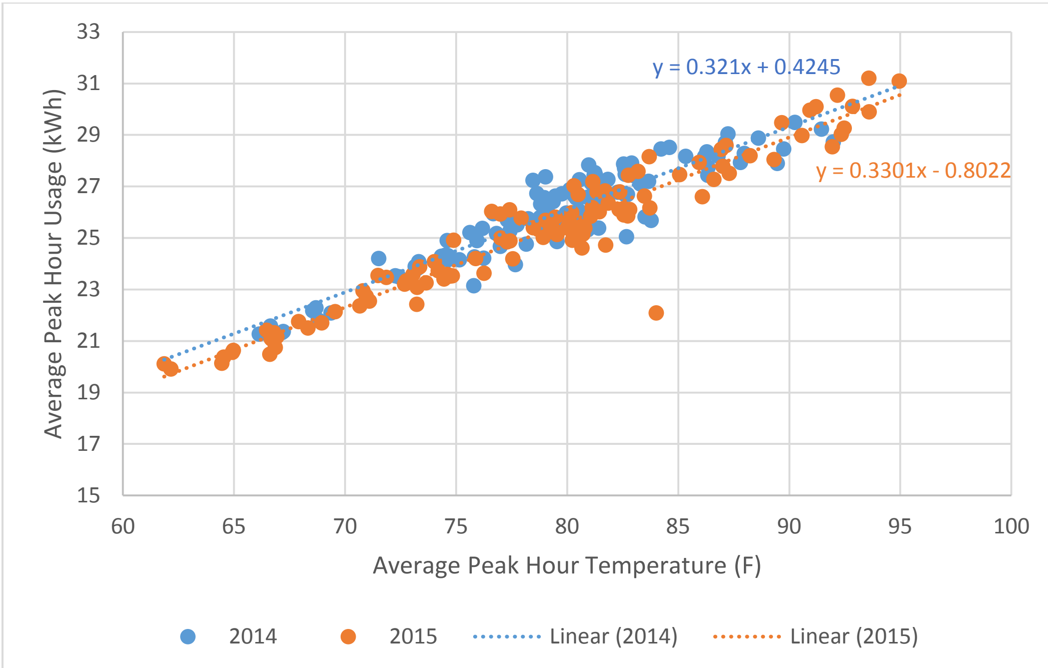
off-peak). The load changes, which are negative for all but one pricing period, do not appear to be explained by the temperature changes across years.

Table 5.2: Medium Business Percent Change in Average Load Levels and Temperatures by Pricing Period

TOU Pricing Period			YoY % Change in Average: Load	YoY % Change in Average: Temperatures
Summer	Weekdays	Peak	-2.3%	-0.7%
		Part-Peak	-2.0%	-0.4%
		Off-Peak	-1.5%	0.0%
	Weekends & Holidays	Off-Peak	-2.1%	-0.6%
Winter	Weekdays	Part-Peak	0.6%	2.5%
		Off-Peak	-0.8%	2.6%
	Weekends & Holidays	Off-Peak	-0.9%	1.0%

Figure 5.3 shows average peak-hour usage plotted against temperatures in the summers of 2014 and 2015. Each data point represents one day. Linear trend lines and corresponding equations are also provided. The figure confirms the temperature and load level differences shown in Figure 5.1 and also illustrates that there was little change in weather sensitivity across years. That is, the slope of the trend lines are very similar for 2014 and 2015. In 2014, on average, a ten degree increase in temperature corresponded to an additional 3.2 kWh usage per peak-hour, whereas a similar increase in temperature during 2015 corresponded to an additional 3.3 kWh usage per hour. On average, for any given temperature, peak-hour usage is 0.38 kWh lower in 2015 relative to 2014.

Figure 5.3: Average Peak Loads and Temperatures for Medium Business Customers, Summer Weekdays



5.2 Estimation Results

As discussed in Section 3.1, the limitation of the simple graphical and statistical comparisons presented in Section 5.1 is that they average across all available days and customers, and thus do not formally account for the effects of factors such as weather conditions or idiosyncratic customer variations. To account for these nuances, we employ a fixed-effects regression model and obtain an estimate of load impacts on an hourly basis. The estimated hourly coefficients can be added to observed loads for TOU customers in the post-TOU period, providing an estimate of the treatment customer reference load, or the load that would have occurred absent TOU rates. Dividing that coefficient by the reference load provides an estimate of the TOU load impact expressed in percentage terms.

Table 5.3 contains estimated hourly reference loads, actual average observed loads, and estimated percent load impacts for summer weekdays and weekends based on fixed-effects regression models. Each of the estimated coefficients used to calculate summer percent load impacts except hour-ending 7 (6:00 to 7:00 a.m.) is statistically significant at the 0.05 (95 percent confidence) level. Table 5.4 displays similar results for the winter period. Several estimated coefficients used to calculate winter percent load impacts are not statistically significant, specifically hours-ending 7 (6:00 to 7:00 a.m.) and 16 to 19 (3:00 to 7:00 p.m.) on weekdays and hours-ending 14 to 17 (1:00 to 5:00 p.m.) on weekends.

Table 5.3: Medium Business Estimated Load Impacts from Hourly Regressions – Summer

	Weekday			Weekend		
Hour	Reference kWh	Observed kWh	% Load Impact	Reference kWh	Observed kWh	% Load Impact
1	11.40	11.24	-1.4%	11.35	11.24	-1.0%
2	10.87	10.74	-1.2%	10.75	10.67	-0.8%
3	10.59	10.48	-1.1%	10.37	10.31	-0.6%
4	10.60	10.45	-1.4%	10.23	10.14	-0.8%
5	11.03	10.86	-1.5%	10.33	10.23	-1.0%
6	12.17	12.02	-1.2%	10.66	10.56	-0.9%
7	13.98	13.89	-0.7%	10.81	10.79	-0.2%
8	16.57	16.44	-0.7%	11.47	11.39	-0.7%
9	19.75	19.55	-1.0%	12.90	12.77	-1.0%
10	22.09	21.77	-1.4%	14.51	14.30	-1.5%
11	23.88	23.49	-1.6%	15.96	15.67	-1.8%
12	25.20	24.75	-1.8%	17.03	16.69	-2.0%
13	25.94	25.45	-1.9%	17.69	17.33	-2.0%
14	26.82	26.29	-2.0%	18.17	17.82	-2.0%
15	27.03	26.48	-2.0%	18.40	18.05	-1.9%
16	26.45	25.89	-2.1%	18.43	18.07	-2.0%
17	25.14	24.58	-2.2%	18.31	17.94	-2.0%
18	22.87	22.34	-2.3%	17.81	17.46	-2.0%
19	20.39	19.93	-2.3%	17.00	16.65	-2.0%
20	18.75	18.36	-2.1%	16.24	15.92	-2.0%
21	17.79	17.41	-2.1%	15.78	15.46	-2.1%
22	16.15	15.80	-2.2%	14.75	14.42	-2.2%
23	13.96	13.70	-1.9%	13.12	12.89	-1.8%
24	12.46	12.25	-1.7%	11.90	11.73	-1.4%
Averages						
Peak	25.71	25.17	-2.1%			
Part Peak	20.50	20.13	-1.8%			
Off Peak	12.36	12.21	-1.3%	14.33	14.10	-1.5%

Table 5.4: Medium Business Estimated Load Impacts from Hourly Regressions – Winter

	Weekday			Weekend		
Hour	Reference kWh	Observed kWh	% Load Impact	Reference kWh	Observed kWh	% Load Impact
1	10.27	10.22	-0.5%	10.43	10.26	-1.7%
2	9.91	9.87	-0.3%	10.03	9.86	-1.7%
3	9.76	9.74	-0.2%	9.25	9.37	1.3%
4	9.85	9.81	-0.4%	9.75	9.57	-1.9%
5	10.27	10.24	-0.4%	9.87	9.70	-1.7%
6	11.51	11.46	-0.4%	10.28	10.13	-1.4%
7	13.77	13.76	-0.1%	10.87	10.78	-0.8%
8	16.08	16.03	-0.3%	11.08	11.02	-0.6%
9	18.63	18.50	-0.7%	11.86	11.79	-0.6%
10	20.03	19.84	-0.9%	12.87	12.79	-0.6%
11	20.81	20.63	-0.9%	13.62	13.56	-0.4%
12	21.21	21.03	-0.8%	14.03	13.98	-0.3%
13	21.25	21.11	-0.7%	14.21	14.16	-0.4%
14	21.61	21.50	-0.5%	14.33	14.31	-0.2%
15	21.49	21.43	-0.2%	14.33	14.34	0.0%
16	20.77	20.76	0.0%	14.24	14.25	0.1%
17	19.65	19.68	0.2%	14.25	14.22	-0.2%
18	18.34	18.34	0.0%	14.49	14.32	-1.1%
19	17.03	17.00	-0.2%	14.42	14.20	-1.5%
20	16.17	16.10	-0.5%	14.06	13.88	-1.3%
21	15.35	15.23	-0.7%	13.61	13.42	-1.4%
22	13.87	13.77	-0.8%	12.73	12.52	-1.7%
23	12.20	12.14	-0.5%	11.59	11.40	-1.6%
24	11.04	11.02	-0.2%	10.74	10.56	-1.7%
Averages						
Peak						
Part Peak	19.02	18.92	-0.5%			
Off Peak	11.47	11.43	-0.3%	12.37	12.27	-0.9%

The average values at the bottom of Tables 5.3 and 5.4 represent average hourly load impacts for each TOU pricing period, and they show that TOU rates lead to energy reductions in all periods in both the summer and winter seasons. The largest reduction, 2.1 percent, occurs during summer peak hours, with slightly smaller reductions during summer part peak hours of 1.8 percent. Both of these reductions are larger than those calculated for off-peak summer hours (1.3 percent on weekdays and 1.5 percent on weekends).

Similar to the results for small businesses described in Section 4.2, the medium business load impacts are not entirely consistent with our expectations for TOU demand response. That is, we would expect customers to reduce usage in higher-priced periods (peak hours), but increase usage (or not change usage) in the lowest-priced periods (off-peak hours. Instead, we estimate usage reductions in all hours. These estimates look more like conservation in response to increased awareness of energy use than TOU demand response to changing price signals.[20]

The average values at the bottom of Tables 5.3 and 5.4 can be compared to those from the simple calculations presented in Table 5.2. Percent load impacts are smaller in both summer and winter seasons using fixed-effects regression, but the pattern across peak, part-peak, and off-peak periods is similar. That is, all periods experience post-TOU load reductions, and in the summer season peak hours have the largest percent load reductions. Table 5.5 summarizes the load impacts calculated or estimated by both methods in all relevant periods.

Table 5.5: Medium Business Comparison of Estimated and Calculated Load Impacts, Two Analysis Methods

TOU Pricing Period			% TOU Load Impact: Simple Differences	% TOU Load Impact: Fixed-Effects Regression
Summer	Weekdays	Peak	-2.3%	-2.1%
		Part-Peak	-2.0%	-1.8%
		Off-Peak	-1.5%	-1.3%
	Weekends & Holidays	Off-Peak	-2.1%	-1.5%
Winter	Weekdays	Part-Peak	0.6%	-0.5%
		Off-Peak	-0.8%	-0.3%
	Weekends & Holidays	Off-Peak	-0.9%	-0.9%

Load impact estimates presented thus far are derived from models that include all sampled medium businesses that transitioned to TOU rates in November 2014. We perform similar analyses on subsets of customers organized by either local capacity area (LCA) or industry group. The primary difference in these models, aside from the subsets of customers included, is that we first *aggregate* the customer-level data by calculating average usage observations across customers in the sub-groups. This approach facilitates running regressions for many sub-groups and allows us to more easily investigate the effect of weather on TOU load impacts by interacting various weather variables with the TOU treatment indicator variable.

Unfortunately, interacting weather variables with the TOU treatment indicator introduced too much variability into load impact estimates and often produced inconsistent and unrealistic results. Most of the estimated coefficients on weather interactions were not statistically significant, and the implied relationship was not consistently positive or negative, either across sub-groups or within sub-group across hours. The ambiguous effect of weather on TOU response is highlighted in Figure 5.3,

[20] However, the fact that peak usage reductions are higher than part-peak, and both of those reductions are higher than off-peak usage reductions is somewhat consistent with TOU demand response.

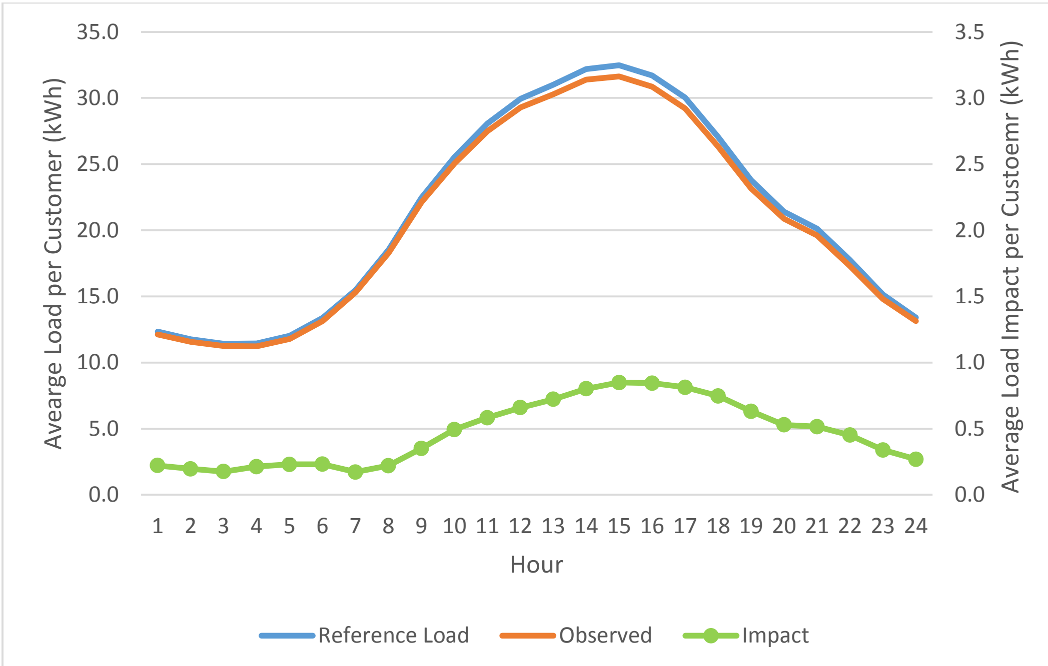
where the slopes of the trend lines are similar in both years, suggesting that the introduction of TOU rates did not affect weather sensitivity.

As a result, when constructing estimated load impacts that correspond to monthly average weekdays and system peak days, in accordance with the CPUC Load Impact Protocols, we opted to estimate the load impacts in percentage terms.[21] That is, the dependent variable in these models is the natural log of average hourly load for the customer group in question (*e.g.,* medium TOU customers in the Greater Bay Area) and the explanatory variables control for weather, hour-of-day, day-of-week, and month-of-year effects. This approach produces dynamic levels of TOU response that are related to load levels on different day types, but not explicitly related to temperatures.

Figure 5.4 illustrates average estimated reference loads, actual observed loads, and estimated load impacts on the 2015 August system peak day for all medium business customers. The usage levels displayed in the graph are similar to those presented in Table 5.3 but higher reflecting different weather conditions on the August system peak day. The average percent load impact during the peak period is -2.6 percent, which is again similar to but slightly higher than those found in the fixed-effects analysis for peak periods during all summer weekdays. In this case, the difference in percentage terms is not due to weather conditions, but is instead due to the difference in methodology as described above (using aggregate load and natural log of kWh as the dependent variable). The same pattern that we found previously for part-peak and off-peak periods holds as well, with average part-peak load impacts of -2.2 percent and off-peak load impacts of -1.7 percent.

[21] We cap hourly percent load impact estimates at +/- 10 percent, as it is likely that any estimated impacts larger than 10 percent are due to exogenous factors rather than the introduction of TOU rates. This constraint is only met for a small share of hours in sub-groups with limited numbers of customers in the small business and agricultural business categories.

Figure 5.4: August System Peak Reference Loads and Load Impacts for All Medium Businesses (Average Per-Customer kWh)

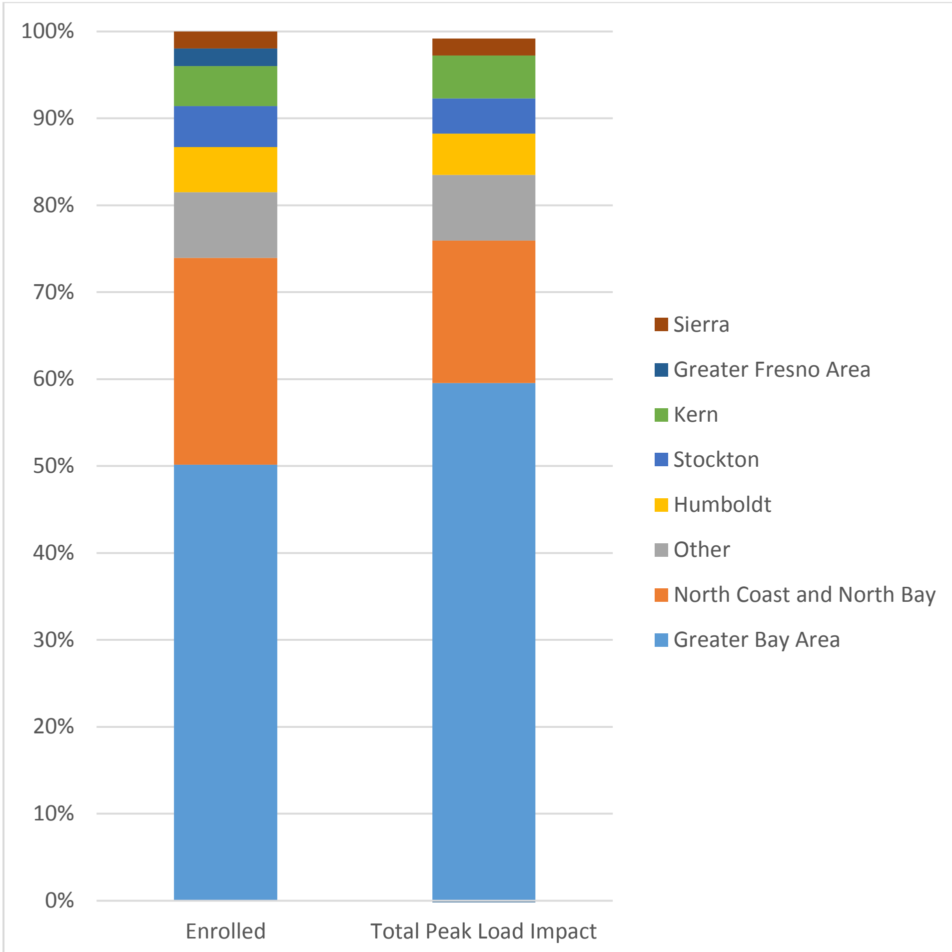


Figures 5.5 and 5.6 illustrate the distribution of total load impacts across LCAs and industry groups, respectively. The left bar represents the distribution of customer enrollments, and the underlying values for the right bar are total load impacts during the peak TOU pricing period (noon to 6 p.m.) under weather conditions that occurred during the August 2015 system peak day.

In Figure 5.5, the largest share of total load impacts and customers comes from the Greater Bay Area, with half of the enrollments and 60 percent of the load impacts. The North Coast and North Bay LCA group contributes the next largest share of load reductions, 17 percent, but makes up 24 percent of the population. The remaining LCAs contribute to load impacts in shares that are similar to their respective portion of the enrollment population.[22]

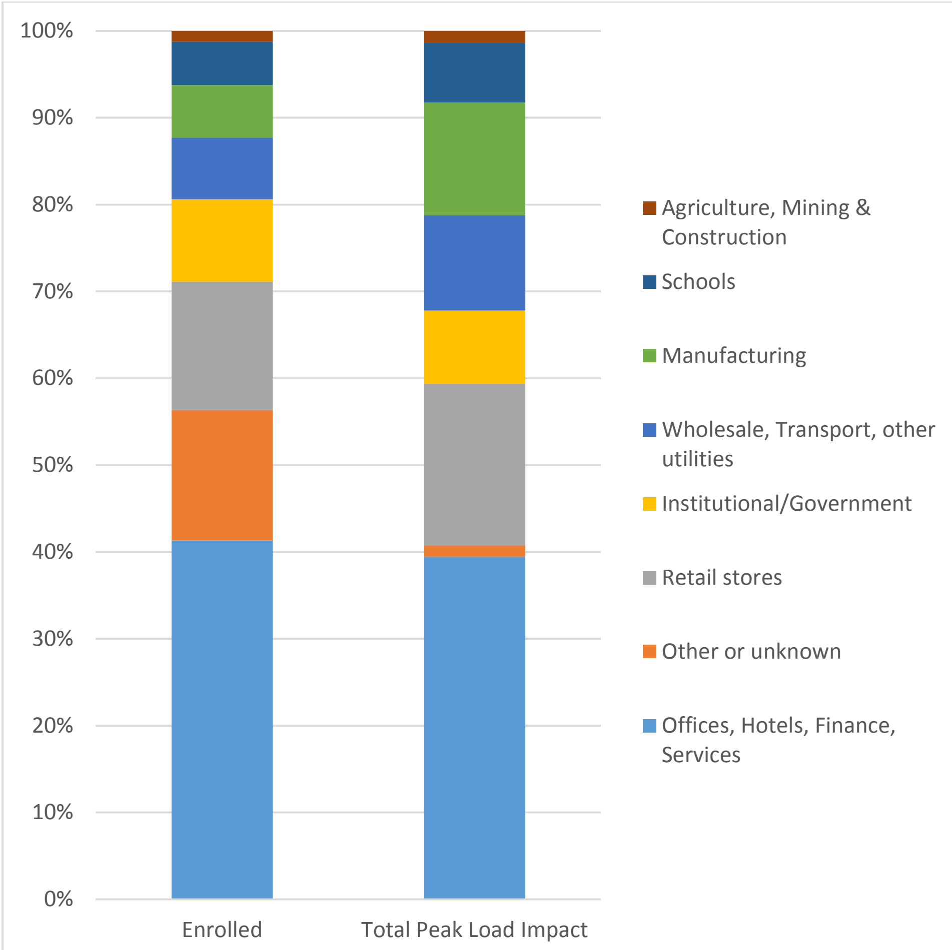
[22] The Greater Fresno Area experiences modest estimated load *increases* (0.8 percent), which is a negative contribution to load reductions and is not presented in the graph.

Figure 5.5: Medium Business August System Peak Distribution of Load Impacts by LCA



In Figure 5.6, the largest share of total load impacts and customers, roughly 40 percent, comes from the "Offices, Hotels, Finance, Services" industry group. The next largest industry group by enrollments is "Other or Unknown", which makes up a 15 percent of the enrolled customers but only contributes one percent of the load impacts. The remaining industries make up for the disparity in the "Other or Unknown" industry group by contributing more than their respective population shares to total load impacts.

Figure 5.6: Medium Business August System Peak Distribution Load Impacts by Industry



6. Agricultural Business Customer Findings

In order to analyze the effect of TOU rates on usage patterns for agricultural business customers, we first compile a set of eligible treatment customers with sufficient pre- and post-treatment interval data (approximately 7,200 out of 8,300 March 205 TOU transitioners). Because of the limited number of newly transitioned TOU customers, we did not sample the population. After applying screens to ensure quality of the data, we retain 6,143 treatment customers. Table 6.1 summarizes the customer counts.

Table 6.1: Numbers of Agricultural Business Treatment Customers

	# Treatment Customers
March 2015 TOU Transitioners	8,304
Eligible for Analysis	7,154
Sampled for Analysis	7,154
Used in Analysis	6,143

6.1 Graphical and Statistical Comparisons of Load Levels

As described in Section 3.1, we conduct several analyses to estimate TOU demand and energy impacts. The first analysis is a simple statistical and graphical comparison of average treatment customer loads and weather conditions during pre-TOU and post-TOU periods. Because agricultural businesses were transitioned to TOU rates in March 2015, there were insufficient post-treatment data available at the time of this evaluation to include winter period results. As such, only summer analyses and results are presented for agricultural customers.

Figure 6.1 shows average weekday load profiles for agricultural businesses before (2014) and after (2015) transitioning to TOU rates during summer periods. Average temperature profiles for each year are also displayed and measured on the secondary axis. There is very little difference in average temperatures from 2014 to 2015, but there is a more pronounced difference in average load levels, particularly in afternoon hours. Specifically, in summer 2015, usage levels are roughly equal to or lower than summer 2014 levels in all hours and lower still during peak hours.

Figure 6.1: Average Loads and Temperatures for Agricultural Business Customers - Summer Weekdays

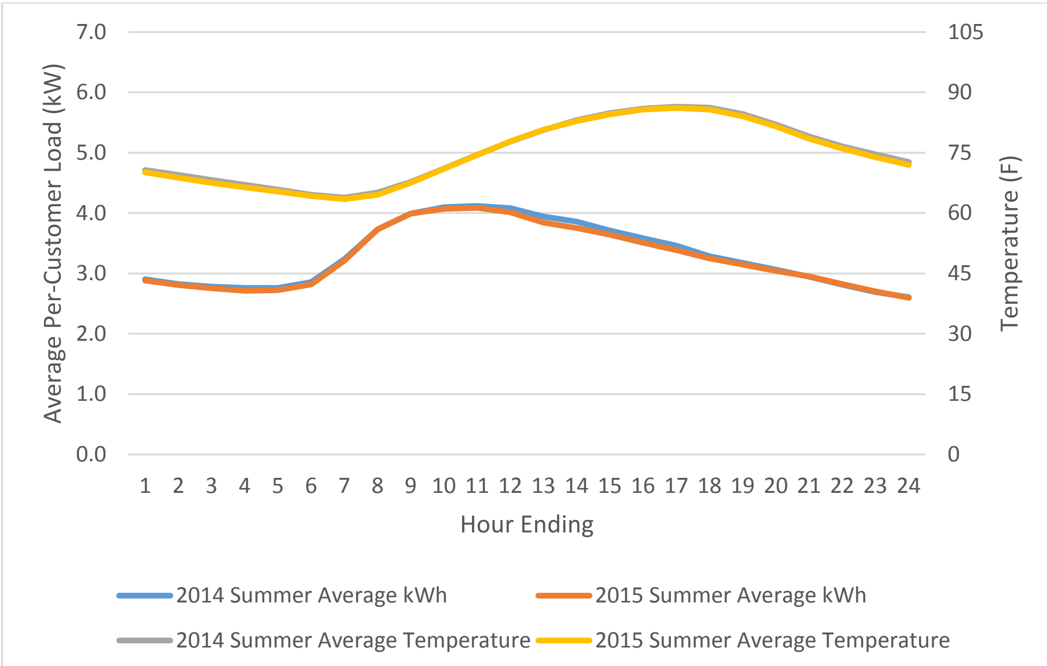


Table 6.2 summarizes percent differences in average load levels and temperatures from summers 2014 to 2015 in terms of TOU pricing period (peak and off-peak).

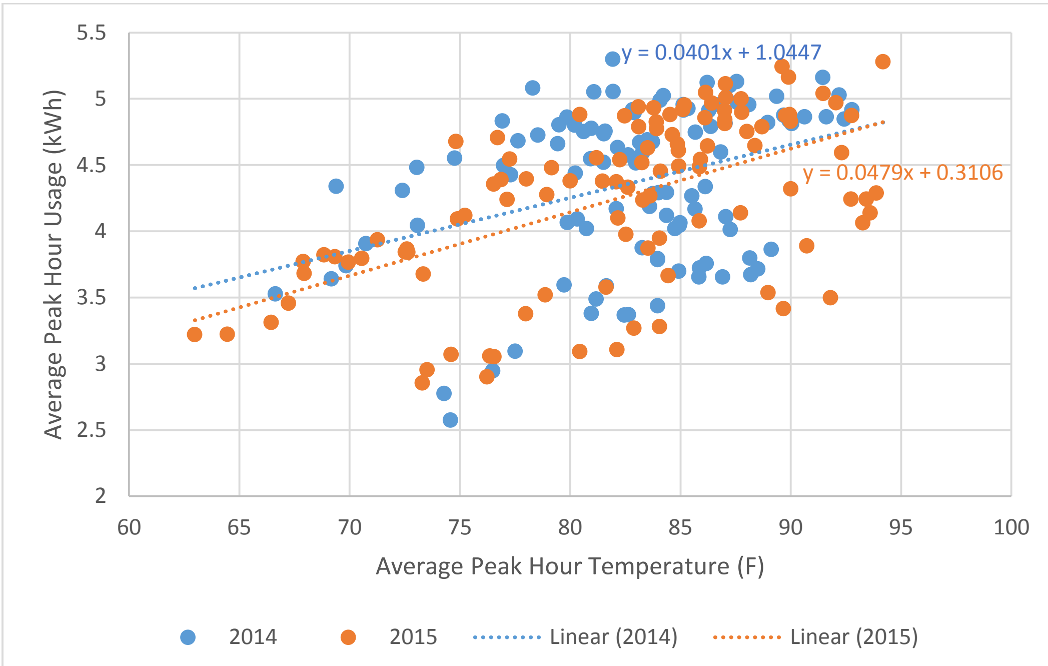
Table 6.2: Agricultural Business Percent Change in Average Load Levels and Temperatures by Pricing Period

TOU Pricing Period			YoY % Change in Average:	
			Load	Temperatures
Summer	Weekdays	Peak	-2.1%	-0.3%
		Off-Peak	-0.6%	-0.7%
	Weekends & Holidays	Off-Peak	-1.0%	-0.6%

Figure 6.2 shows average peak-hour usage plotted against temperatures in the summers of 2014 and 2015. Each data point represents one day. Linear trend lines and corresponding equations are also provided. As expected, there is a positive relationship between temperatures and usage levels, however there is much more variation for agricultural customers relative to small and medium businesses (see Figures 4.3 and 5.3). That is, there is much more dispersion (error) around the trend line, suggesting that agricultural load levels are less determined by temperatures relative to other customer groups. Additionally, unlike small and medium businesses, the slopes of the trend lines suggest that weather sensitivity may have changed after the introduction of

TOU rates. In 2014, a ten degree increase in temperature corresponded to an additional 0.40 kWh usage per peak-hour, whereas a similar increase in temperature during 2015 corresponded to an additional 0.48 kWh usage per hour.

Figure 6.2: Average Peak Loads and Temperatures for Small Business Customers, Summer Weekdays



6.2 Estimation Results

As discussed in Section 3.1, the limitation of the simple graphical and statistical comparisons presented in Section 6.1 is that they average across all available days and customers, and thus do not formally account for the effects of factors such as weather conditions or idiosyncratic customer variations. To account for these nuances, we employ a fixed-effects regression model and obtain an estimate of load impacts on an hourly basis. The estimated hourly coefficients can be added to observed loads for TOU customers in the post-TOU period, providing an estimate of the treatment customer reference load, or the load that would have occurred absent TOU rates. Dividing that coefficient by the reference load provides an estimate of the TOU load impact expressed in percentage terms.

Table 6.3 contains estimated hourly reference loads, actual average observed loads, and estimated percent load impacts for summer weekdays and weekends based on fixed-effects regression models. Only half of the estimated coefficients used to calculate summer weekday percent load impacts are statistically significant at the 0.05 (95 percent confidence) level.[23]

Table 6.3: Agricultural Business Estimated Load Impacts from Hourly Regression – Summer

	Weekday			Weekend		
Hour	Reference kWh	Observed kWh	% Load Impact	Reference kWh	Observed kWh	% Load Impact
1	2.82	2.85	1.1%	2.86	2.88	0.8%
2	2.75	2.78	1.0%	2.78	2.81	1.1%
3	2.72	2.74	0.8%	2.74	2.76	0.7%
4	2.70	2.70	0.2%	2.71	2.71	0.0%
5	2.71	2.71	0.0%	2.72	2.72	0.2%
6	2.85	2.86	0.5%	2.82	2.82	0.0%
7	3.43	3.46	1.0%	3.19	3.21	0.5%
8	4.18	4.30	2.7%	3.68	3.73	1.3%
9	4.60	4.71	2.3%	3.94	3.99	1.2%
10	4.75	4.84	1.8%	4.05	4.07	0.6%
11	4.82	4.88	1.3%	4.07	4.08	0.4%
12	4.81	4.82	0.1%	4.03	4.01	-0.4%
13	4.64	4.55	-1.9%	3.89	3.84	-1.2%
14	4.61	4.49	-2.7%	3.81	3.75	-1.5%
15	4.51	4.38	-2.9%	3.66	3.64	-0.6%
16	4.36	4.22	-3.3%	3.54	3.51	-0.9%
17	4.13	4.03	-2.4%	3.41	3.39	-0.7%
18	3.89	3.85	-1.1%	3.24	3.25	0.2%
19	3.80	3.80	-0.1%	3.13	3.15	0.6%
20	3.69	3.71	0.4%	3.02	3.04	0.8%
21	3.55	3.59	1.1%	2.90	2.95	1.7%
22	3.39	3.43	1.3%	2.77	2.83	2.1%
23	3.23	3.26	1.2%	2.65	2.70	2.1%
24	3.09	3.11	0.7%	2.56	2.60	1.4%
Averages						
Peak	4.36	4.25	-2.4%			
Off Peak	3.55	3.59	1.0%	3.26	3.27	0.4%

The average values at the bottom of Table 4.3 represent average hourly load impacts for each TOU pricing period, and they show that TOU rates lead to energy reductions of 2.4 percent in the peak period and load increases of one percent in the off-peak period.

Contrary to our findings for small and medium businesses, the agricultural load impact estimates are consistent with our expectations for TOU demand response. That is, we

[23] For the summer weekday model, statistically significant coefficients are estimated for hours-ending: 8, 9, 10, 11, 13, 14, 15, 16, 17, 21, 22, and 23. Only four of the estimated coefficients used to calculate summer weekend percent load impacts are statistically significant, hours-ending: 14, 21, 22, and 23.

expect customers to reduce usage in higher-priced periods (peak hours), but increase usage (or not change usage) in the lowest-priced periods (off-peak hours).

Table 6.4 compares the average values at the bottom of Table 6.3 to those from the simple calculations presented in Table 6.2. Both methods produce similar peak period load reduction estimates of 2.1 and 2.4 percent, but where the simple differences method shows modest load reductions in other periods, the fixed-effects regression produces estimates of load increases in off-peak periods.

Table 6.4: Agricultural Business Comparison of Estimated and Calculated Load Impacts, Two Analysis Methods

TOU Pricing Period			% TOU Load Impact: Simple Differences	% TOU Load Impact: Fixed-Effects Regression
Summer	Weekdays	Peak	-2.1%	-2.4%
		Off-Peak	-0.6%	1.0%
	Weekends & Holidays	Off-Peak	-1.0%	0.4%

Load impact estimates presented thus far are derived from models that include all agricultural businesses that transitioned to TOU rates in March 2015. We perform similar analyses on subsets of customers organized by either local capacity area (LCA) or industry group. The primary difference in these models, aside from the subsets of customers included, is that we first *aggregate* the customer-level data by calculating average usage observations across customers in the sub-groups. This approach facilitates running regressions for many sub-groups and allows us to more easily investigate the effect of weather on TOU load impacts by interacting various weather variables with the TOU treatment indicator variable.

Unfortunately, interacting weather variables with the TOU treatment indicator introduced too much variability into load impact estimates and often produced inconsistent and unrealistic results. Most of the estimated coefficients on weather interactions were not statistically significant, and the implied relationship was not consistently positive or negative, either across sub-groups or within sub-group across hours.

As a result, when constructing estimated load impacts that correspond to monthly average weekdays and system peak days, in accordance with the CPUC Load Impact Protocols, we opted to estimate the load impacts in percentage terms.[24] That is, the

[24] We cap hourly percent load impact estimates at +/- 10 percent, as it is likely that any estimated impacts larger than 10 percent are due to exogenous factors rather than the introduction of TOU rates. This constraint is only met for a small share of hours in sub-groups with limited numbers of customers in the small business and agricultural business categories.

dependent variable in these models is the natural log of average hourly load for the customer group in question (*e.g.,* agricultural customers in the Greater Bay Area) and the explanatory variables control for weather, hour-of-day, day-of-week, and month-of-year effects. This approach produces dynamic levels of TOU response that are related to load levels on different day types, but not explicitly related to temperatures.

Figure 6.3 illustrates average estimated reference loads, actual observed loads, and estimated load impacts on the 2014 August system peak day for all agricultural business customers. The usage levels displayed in the graph are similar to those presented in Table 6.3 but higher reflecting different weather conditions on the August system peak day. The average percent load impact during the peak period is -2.5 percent, which is again similar to but slightly higher than those found in the fixed-effects analysis for peak periods during all summer weekdays. The same pattern that we found using fixed-effects regression for off-peak periods holds as well, with average off-peak load increases of 0.9 percent.

Figure 6.3: August System Peak Reference Loads and Load Impacts for All Agricultural Businesses (Average Per Customer kWh)

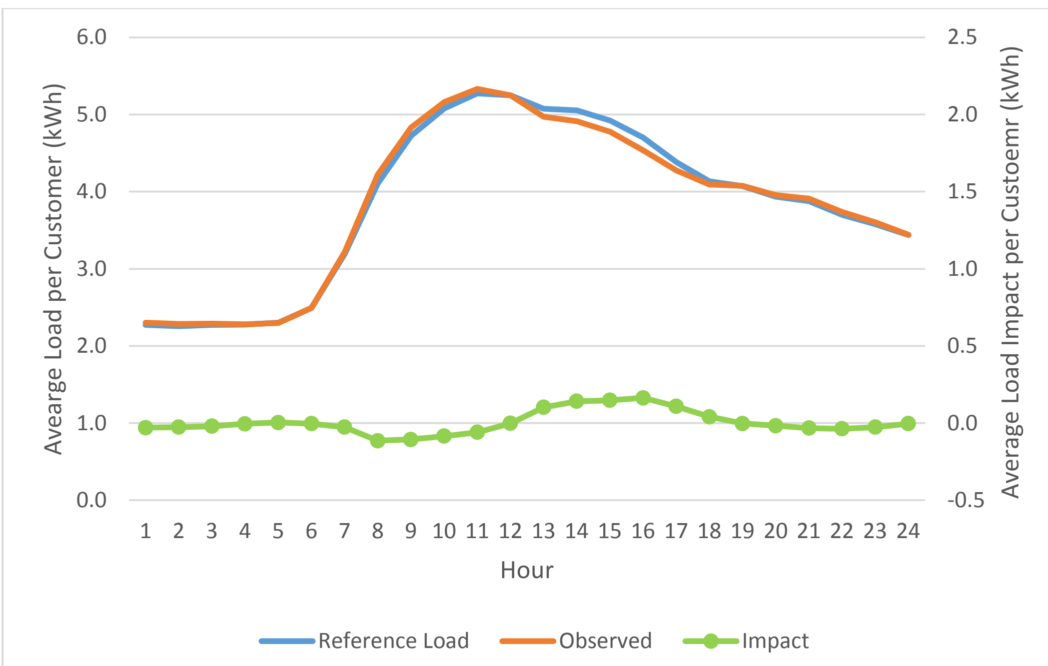


Figure 6.4 illustrates the distribution of total load impacts across LCAs. The left bar represents the distribution of customer enrollments, and the underlying values for the right bar are total load impacts during the peak TOU pricing period (noon to 6 p.m.) under weather conditions that occurred during the August 2015 system peak day.

There are two LCAs, “Greater Bay Area” and “Greater Fresno Area”, with estimated TOU load *increases* of one and 1.7 percent, respectively, during the peak period. While those percentage increases are rather modest, when taken together with the number of enrolled customers in each LCA, the contribution to total load impacts are substantial. Without these two LCAs, total load impacts during the August 2015 system peak day for agricultural businesses would be over 7 MW, however including the two LCAs leads to total load impacts for agricultural businesses of 6.35 MW. As such, Figure 6.4 shows each LCAs share of the enrolled customers but only shows the share of total load impacts for LCAs that experience load reductions.

In Figure 6.4, the largest share of customers and total load impacts, 45 and 40 percent, respectively, comes from the “Other” LCA group. Greater Fresno makes up 28 percent of enrollments, but estimated load *increases* for that LCA add up to seven percent of the total load impacts and are not shown on the graph. Stockton contributes the next largest share of load reductions, 26 percent, but makes up nine percent of the population. The remaining LCAs contribute to shares of enrollments and load impacts in roughly proportional shares. Note that the contents of the figure have been removed due to confidentiality concerns.

Figure 6.4: Agricultural Business August System Peak Distribution of Load Impacts by LCA

[redacted]

Not surprisingly, but unlike similar distributions for small and medium-sized businesses, the distribution of customers and total load impacts by industry is much different for agricultural businesses in that almost all (97 percent) of the customers are in the "Agriculture, Mining & Construction" industry group. [redacted] Note that additional details have been removed due to confidentiality concerns.

7. *Ex-ante* Load Impact Forecast

Ex-ante load impacts were separately developed for two sets of non-residential customers:

- *Incremental customers*. This customer group consists of customers who will be transitioned to TOU rates in the coming years, or customers who will be new to PG&E and will be placed on a TOU rate by default. The load impacts for this group will affect PG&E's system load going forward. [25]
- *Embedded customers*. These customers have been on TOU rates in the past, so their load impacts are embedded in PG&E's system load and will not lead to additional future load changes. The embedded customer group includes customers who have been on TOU rates for many years as well as customers who were transitioned to TOU rates prior to the 2013 and 2014 program years.

The *ex-ante* methods and results are presented separately for each of these groups.

7.1 Incremental TOU Load Impact Forecast

Methodology

There are three sources of incremental TOU load impacts in the forecast period:

- Transitions of SMB customers in November 2015 and November 2016;
- Transitions of agricultural customers in March 2016 and March 2017; and
- The addition of new customers over time, which are now defaulted directly to TOU rates.

In each of these cases, *ex-post* load impacts serve as the basis for the per-customer load impacts within size group and LCA. For the SMB customers, we use the 2015 *ex-post* load impacts associated with customers transitioned in November 2014. For agricultural

[25] The incremental ex-ante load impact forecast includes non-agricultural small customers, non-agricultural medium customers, and all agricultural customers (regardless of size) -- Non-agricultural large customers are not included in the load impact forecast. Any discrepancies between the sum of small and medium forecasted enrollments and total enrollments in the load impact forecast are due to the inclusion of large agricultural customers in the agricultural load impact forecast.

customers, we use the 2015 *ex-post* load impacts estimated for customers transitioned in March 2015.

Using models that match the *ex-post* models described at the end of Section 3.3, we first develop "observed" loads for each cell (defined as a size group / LCA combination) and each of four distinct weather scenarios, which are distinguished by:

- 1-in-2 weather conditions versus 1-in-10 weather conditions; and
- Whether the peak conditions are determined using the utility's peak or the utility's load at the time of CAISO's peak. We refer to the former as the "utility-specific" scenarios and the latter as "CAISO-coincident" scenarios.

The weather conditions for each scenario were provided to us by PG&E.

The load impacts for each cell and scenario are also derived from the *ex-post* models described at the end of Section 3.3. Specifically, these models estimate a stand-alone TOU load impact in percentage terms (via a dependent variable in natural log form). We apply those hourly percent load impacts to the simulated observed loads for each cell, *c*, and weather scenario, *s*, to arrive at per-customer load impacts expressed in level (kWh) terms.

$$\textit{Load impact}_{c,s} = b_c^{TOU} \times \textit{Simulated Observed Load}_{c,s}$$

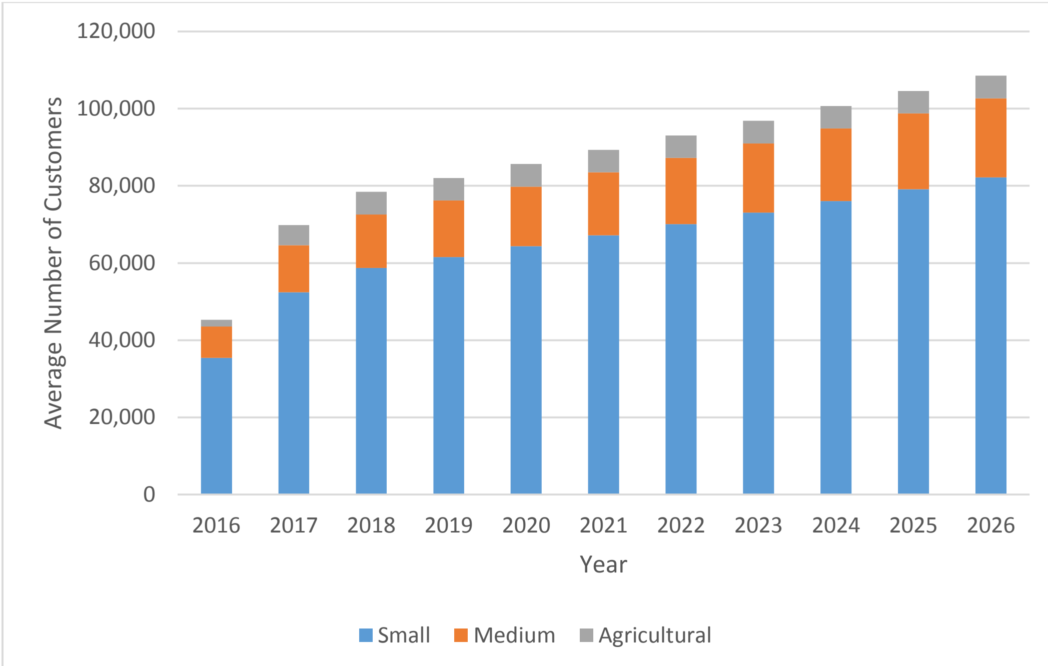
The reference loads (*i.e.*, the loads that would have occurred in the absence of the TOU prices) are simulated by adding the simulated load impacts back into the simulated observed TOU loads.

Results

Figure 7.1 shows the incremental customer TOU enrollments by year for SMB and agricultural customers, where each year shows an average across months. The large increase between 2016 and 2017 is due to the transition of approximately 21,000 SMB customers to TOU rates in November 2016 and 3,800 agricultural customers in March 2017.[26] The remaining growth over time represents new customers that are placed on TOU rates by default.

[26] After the two upcoming waves of agricultural customer transition to TOU rates in 2016 and 2017, we hold the total agricultural enrollment value of 5,853 constant for the remainder of the forecast period.

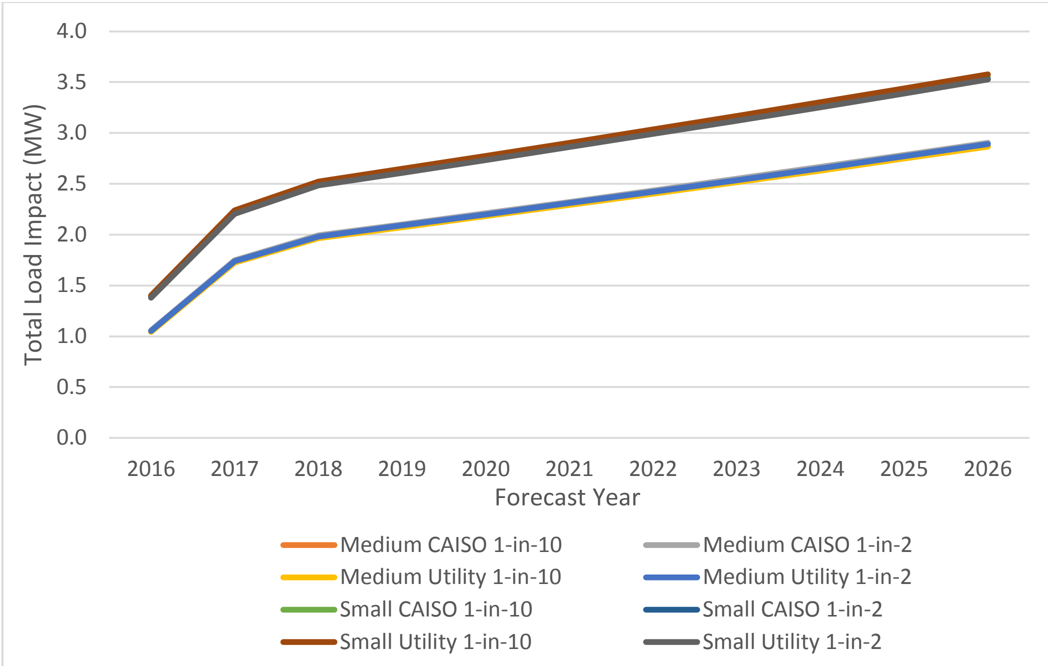
Figure 7.1: Non-Residential TOU Enrollments, Incremental SMB Customers



Figures 7.2 and 7.3 show the January and August (respectively) load impacts by year, customer group, and weather scenario. The load impacts are averaged across 1:00 to 6:00 p.m. for August and 4:00 to 9:00 p.m. for January. In our methods, the load impacts per customer remain constant over time (within size group and LCA), so the change in load impacts over time reflects increases in enrollments.[27]

[27] Because agricultural business load impacts are relatively small in the summer, zero during the winter season, and unchanging after 2017, they are not included in Figures 7.2 and 7.3.

Figure 7.2: January Peak Day *Ex-ante* Load Impacts by Group and Weather Scenario



A comparison of Figures 7.2 and 7.3 indicates that load impacts are higher in August than January. For example, in the 2017 utility-specific 1-in-2 peak forecast, load impacts are 11.5 MW higher in August than in January (combining across the small and medium customer groups).

Figure 7.3: August Peak Day *Ex-ante* Load Impacts by Group and Weather Scenario

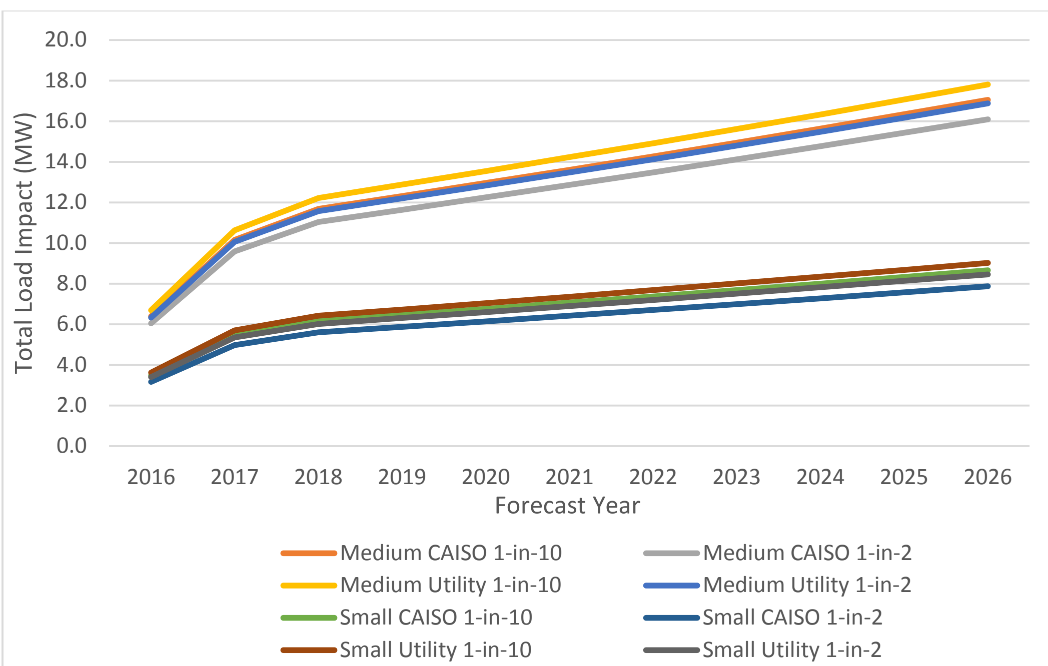


Figure 7.4 provides an illustration of the hourly reference loads, observed loads, and load impacts for the August 2017 utility-specific 1-in-2 peak day. Load reductions are forecast for each hour of the day, with the percentage reduction ranging from 0.6 percent in hour-ending 7 (6:00 to 7:00 a.m.) to 3.0 percent in hour-ending 16 (3:00 to 4:00 p.m.).

Figure 7.4: Hourly *Ex-ante* Load Impacts, All Incremental Customers, August 2017 Utility 1-in-2 Peak Day

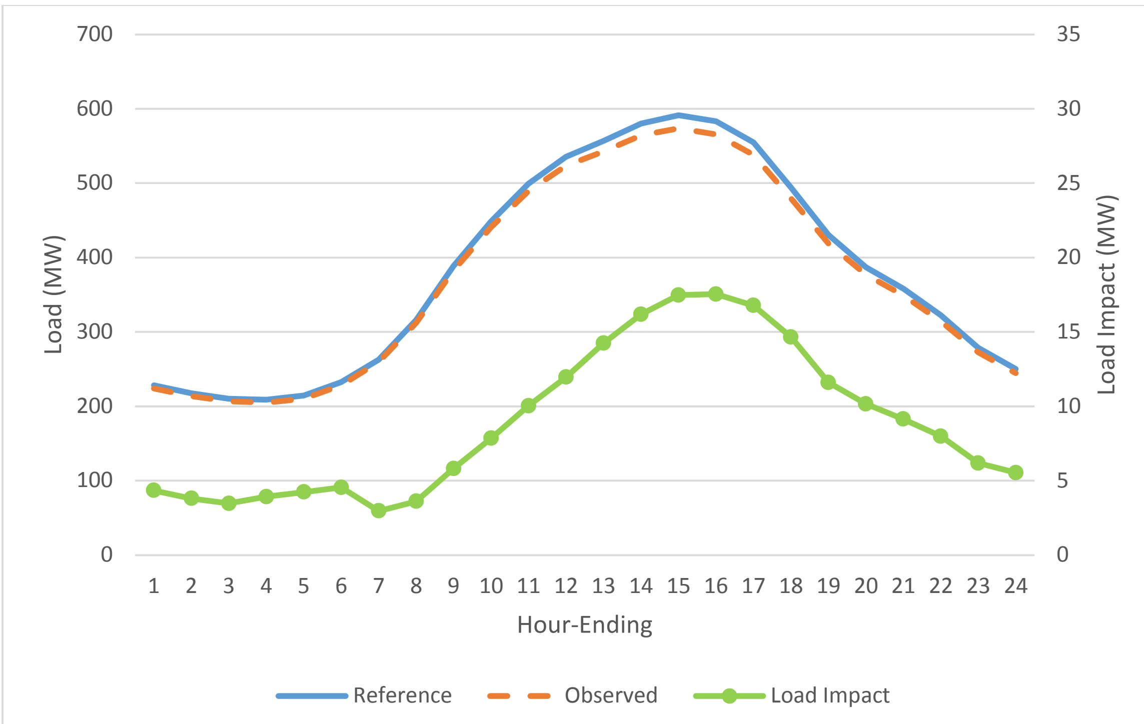
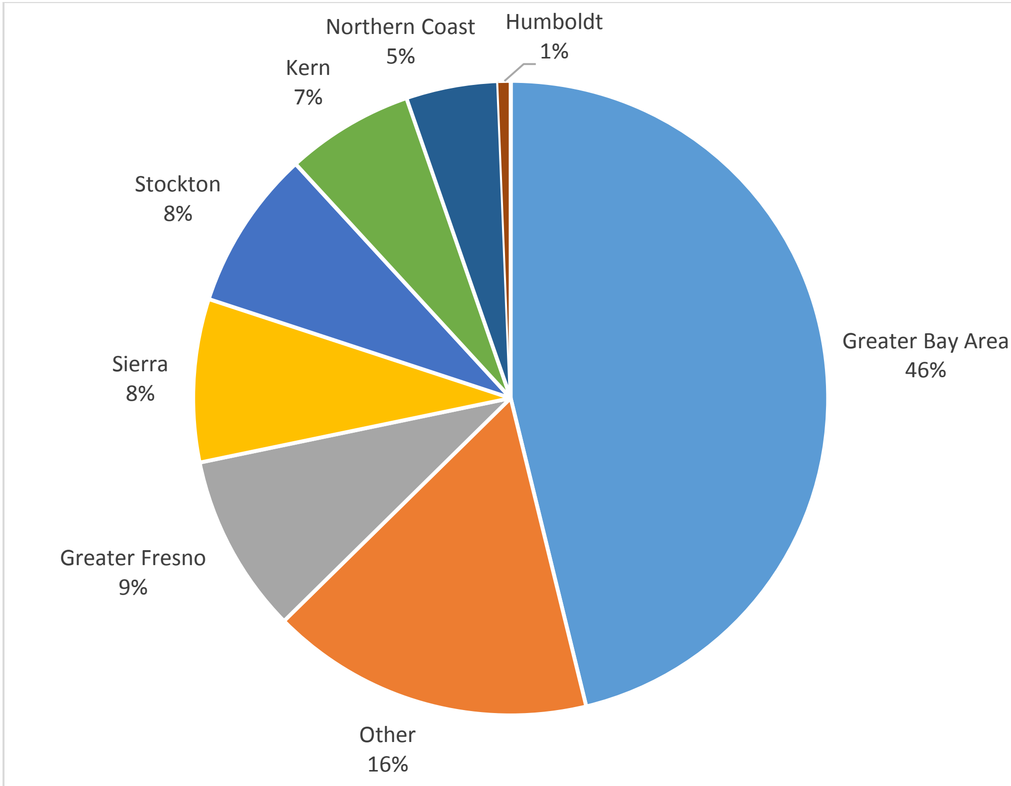


Figure 7.5 shows the distribution of August 2017 load impacts by LCA. The Greater Bay Area LCA accounts for the largest share with 46 percent of total peak day load impacts.

Figure 7.5: August 2017 Peak Day Load Impacts by LCA, Utility-Specific 1-in-2 Weather



7.2 Embedded TOU Load Impact Forecast

Methodology

In contrast to the incremental TOU load impact forecast, the embedded TOU load impact forecast remains constant across the forecast years. That is, there is assumed to be a set of currently enrolled customers that have embedded TOU load impacts (meaning they are already reflected in the customer's load profile and, by extension, PG&E's system load profile), and those load impacts are carried forward through the forecast period.

Two types of customers are present in the embedded TOU load impact forecast: customers who have been on TOU rates for many years (typically large customers on E-19 or E-20 tariffs) and customers who have been transitioned to TOU rates in recent years. A description of our *ex-ante* methods for each group follows.

For the customers who have been on TOU rates for many years, we cannot estimate *ex-post* load impacts because these customers have not been observed on non-TOU rates. Therefore, load impacts for these customers have been simulated using existing studies of TOU demand response. For consistency across studies, we have carried forward the analysis of these customers from the previous study (conducted following the 2014 program year), which itself was based on a previous study (conducted following the 2014 program year). For the program year 2014 study, we needed to adjust the prior forecast to account for changes in the *ex-ante* weather scenarios. That is, PG&E updated its 1-in-2 and 1-in-10 weather definitions prior to the PY 2014 analysis and also added scenarios that correspond to CAISO-coincident conditions. These adjustments were made by adjusting the cell-specific load profiles to account for differences in *ex-ante* weather conditions, where the amount of the adjustment is based on cell-specific estimates of the effect of weather (daily cooling and heating degree hours) on loads.[28]

For the recently transitioned customers, the *ex-ante* load impacts are based on our SMB *ex-post* forecast for customers transitioned in November 2014.[29] The methods follow those used to develop the incremental TOU load impact forecast described in Section 7.1, but applying a different set of enrollments.

Results

The enrollment forecast contains 480,657 embedded TOU customers. Of these, 79,860 were added since the enrollment forecast from the previous program year. We assume that the customer counts present in the previous enrollment forecast (of which there are 400,797) were incorporated into the previous study's embedded TOU *ex-ante* forecast. Therefore, this set of enrollments is applied to our first method described above (the manipulation of the prior study's embedded forecast). The customers added to the enrollment forecast since the previous program year (of which there are 79,860) are applied to our second method described above (based on the *ex-post* load impacts for recently transitioned customers). The two sets of customers are combined for reporting purposes. Figure 7.6 illustrates the enrollments by group.

[28] The data for these estimates were drawn from the previous study's *ex-ante* forecast. For example, each cell has simulated reference loads and load impacts for 48 scenarios (average weekdays and peak month days by month for 1-in-2 and 1-in-10 weather years). We regress the average daily load as a function of CDH, HDH, and monthly indicator variables. The adjustment applied to the reference load is equal to the estimated weather effect multiplied by the difference between the new and old weather variables.
[29] Agricultural business customers are not separately identified in the *ex-ante* embedded results.

Figure 7.6: Embedded TOU Customer Enrollments by Group

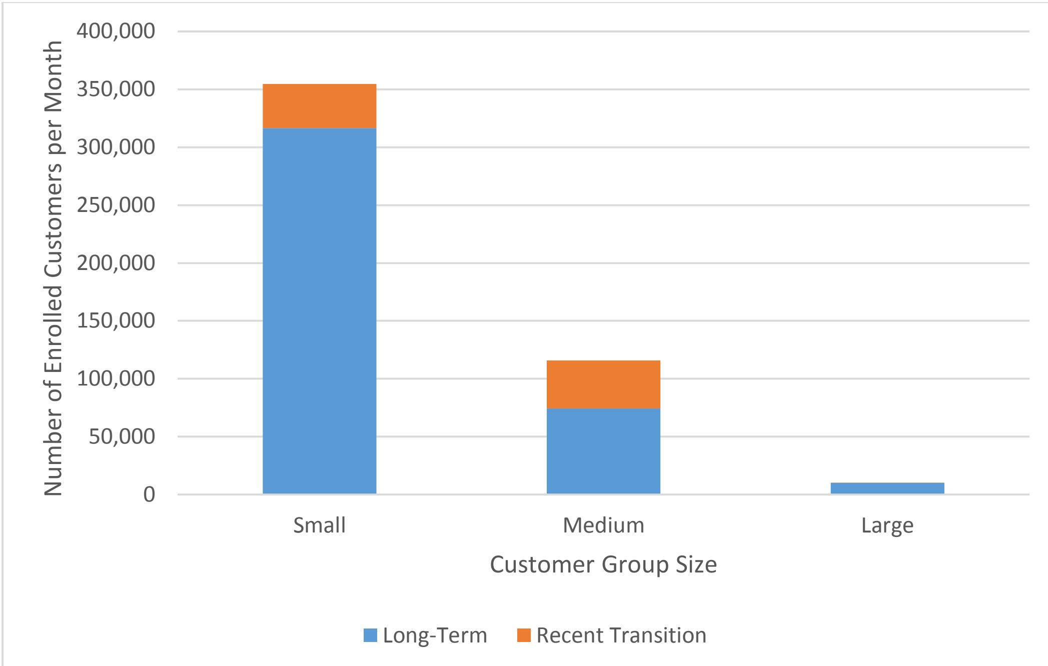


Figure 7.7 shows the monthly embedded TOU load impacts for each weather scenario. The load impacts are averaged across 1:00 to 6:00 p.m. for April through October and 4:00 to 9:00 p.m. for November through March. Summer load impacts range from 300 to 350 MW and winter load impacts are approximately 55 MW. As expected, the utility-specific 1-in-10 peak day load impacts are the highest in the summer.

Figure 7.7: Embedded TOU Load Impacts by Month and Weather Scenario

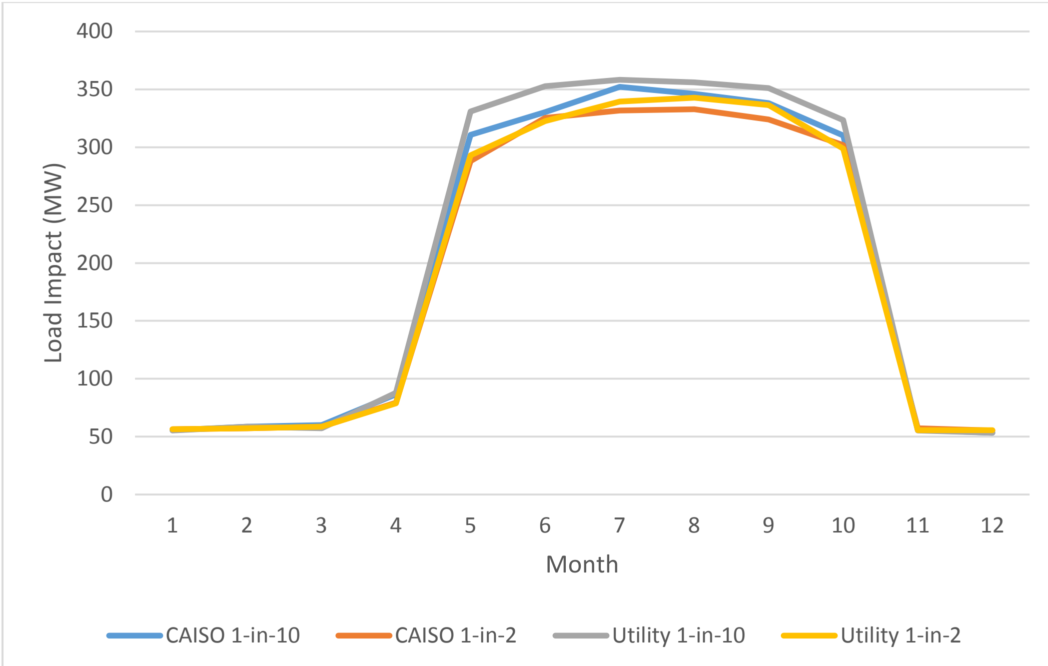


Figure 7.8 shows the distribution of embedded TOU load impacts by LCA, using the August utility-specific 1-in-2 peak day scenario. The Greater Bay Area has the largest share of load impacts.

Figure 7.8: Embedded TOU Load Impacts by LCA, August 2017 Utility 1-in-2 Peak Day

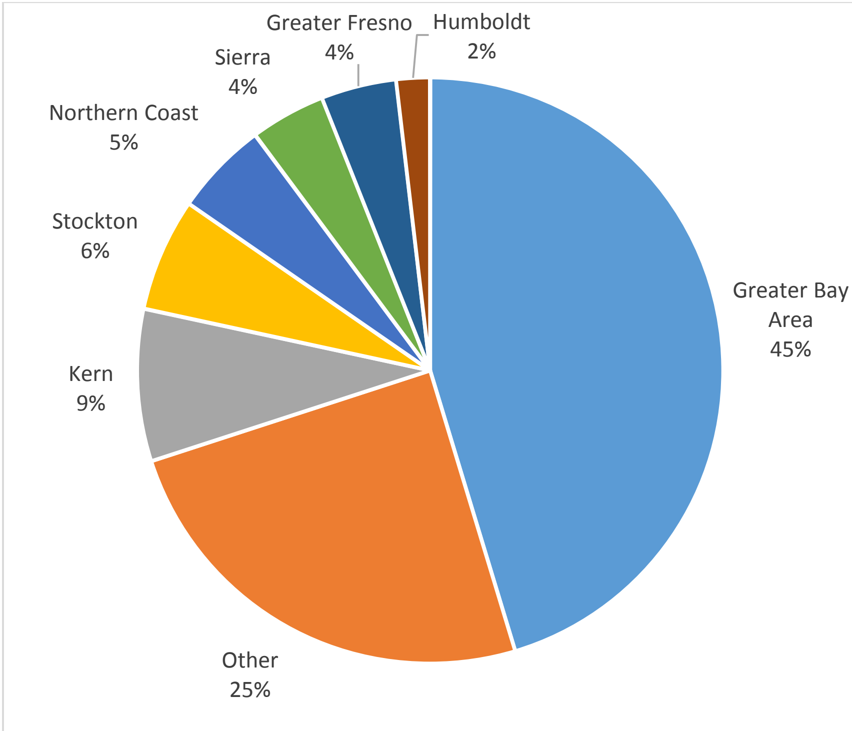
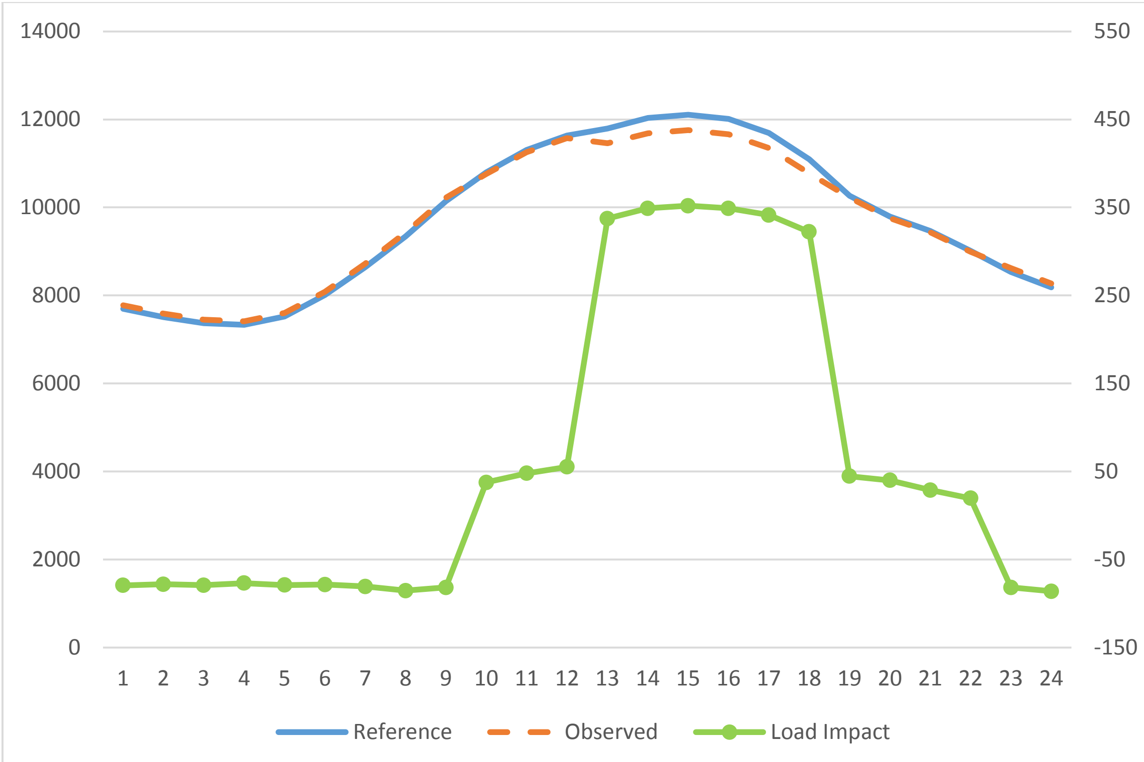


Figure 7.9 shows the hourly reference loads, observed loads, and load impacts for the August utility-specific 1-in-2 peak day. You can see the effect of the simulated embedded load impacts, which contain load reductions during peak hours and load increases in off-peak hours. This pattern of TOU demand response is typical of TOU studies and what one would expect based on the change in the price signals (which increase the price during peak hours and decrease it during off-peak hours). As described in Sections 4 and 5, our *ex-post* estimates for recently transitioned SMB customers have tended to differ from this pattern, often displaying load reductions across all pricing periods.

Figure 7.9: Hourly Embedded TOU Load Impacts, August 2017 Utility 1-in-2 Peak Day



8. Comparisons of Results

In this section, we present and describe various differences in load impacts, including combinations of comparisons of the previous and current studies as well as *ex-post* versus *ex-ante* load impacts. Note that the previous study did not include an *ex-post* study of agricultural customers.

8.1 Previous versus current ex-post

Table 8.1 compares the *ex-pos*t load impacts from the previous and current studies. The summer values represent the August peak day hourly averages from 1:00 to 6:00 p.m. (to match the resource adequacy window). The non-summer values represent the January peak day averages from 4:00 to 9:00 p.m. There are fewer than half of the small-sized customers included in the current study relative to the previous year. In the summer period, the average customer size is slightly higher in the current study along with the per-customer load impacts and the percentage load impacts. In the winter period, average customer size is slightly lower but per-customer load impacts are similar, leading to higher percentage load impacts.

Table 8.1 Current vs. Previous *Ex-post* Load Impacts, *Under 20kW*

Season	Result	Previous Study (Under 20kW)	Current Study (Under 20kW)
Both	# SAIDs	80,019	38,091
Summer	Reference (MW)	206	107
	Load Impact (MW)	5	3
	Per-SAID reference (kW)	2.58	2.82
	Per-SAID load impact (kW)	0.06	0.09
	% Load Impact	2.6%	3.2%
Non-summer	Reference (MW)	126	58
	Load Impact (MW)	3	1
	Per-SAID reference (kW)	1.58	1.54
	Per-SAID load impact (kW)	0.04	0.04
	% Load Impact	2.2%	2.5%

Table 8.2 provides the same comparisons for the medium-sized customers. There are three times as many medium-sized customers in the current year's study relative to the previous year. In both seasons, average customer usage levels are substantially higher in the current year. Per-customer load impacts in the summer are twice as large as those from the previous year, but when combined with higher overall usage, the load impact levels produce only slightly higher percentage load impacts in the current year. In the winter period, the average customer is also substantially larger in the current year, but per-customer load impacts and percentage load impacts are much smaller.

Table 8.2 Current vs. Previous *Ex-post* Load Impacts, *20 to 200kW*

Season	Result	Previous Study (20 to 200kW)	Current Study (20 to 200kW)
Both	# SAIDs	7,442	23,393
Summer	Reference (MW)	140	718
	Load Impact (MW)	3	19
	Per-SAID reference (kW)	18.8	30.7
	Per-SAID load impact (kW)	0.4	0.8
	% Load Impact	2.3%	2.6%
Non-summer	Reference (MW)	78	392
	Load Impact (MW)	4	3
	Per-SAID reference (kW)	10.5	16.8
	Per-SAID load impact (kW)	0.5	0.1
	% Load Impact	4.8%	0.8%

8.2 Previous versus current ex-ante

Table 8.3 compares the incremental *ex-ante* load impact forecasts from the previous and current studies. In each case, the information represents August 2017 peak day hourly averages from 1:00 to 6:00 p.m. with utility-specific 1-in-2 weather conditions for all customers. The current study includes many fewer customers (70,563 versus

167,324), but the average customer reference load, per-customer load impact, and percentage load impact are all larger in the current study.

Table 8.3 Previous vs. Current *Ex-ante* Incremental Load Impacts

Result	Previous *Ex-ante*, Incremental	Current *Ex-ante*, Incremental
# SAIDs	167,324	70,563
Reference (MW)	933	561
Load Impact (MW)	23.3	16.5
Per-SAID reference (kW)	5.6	7.95
Per-SAID load impact (kW)	0.14	0.23
% Load Impact	2.5%	2.9%

In each study, the incremental *ex-ante* load impacts are based on the *ex-post* load impacts. Table 8.4 shows the *ex-post* percentage load impacts for the summer peak period by rate group from each study. Recall that the previous *ex-post* study did not included agricultural customers, therefore we applied the *ex-post* load impacts from the previous study (PY 2013) to agricultural customers in last year's *ex-ante* incremental analysis.

Table 8.4: Comparison of Summer Peak Percentage Load Changes

Customer Group	Previous *Ex-post*	Current *Ex-post*
Small (Under 20kW)	2.1%	3.2%
Medium (20 to 200kW)	2.4%	2.6%
Agricultural	N/A	2.6%

8.3 Previous ex-ante versus current ex-post

Table 8.5 compares the previous study's August peak day 2015 *ex-ante* incremental load impacts for utility 1-in-2 weather year to the *ex-post* load impacts estimated in this study. The previous forecast enrollment was slightly higher (71,380 versus 69,788), but the per-customer reference load, load impact, and percentage load impact are substantially higher in the current year's *ex-post* analysis. Much of the difference is probably due to the disproportionate share of the current year's study participants in the medium size group and the larger average size of medium group customers. Last year's study forecast 23 percent of August 2015 enrollments in the medium size group, while the current year's *ex-post* analysis is 34 percent medium. As highlighted in Table 8.2, the current year's medium-sized customers are 60 percent larger than the previous year's medium customers.

Table 8.5 Previous *Ex-ante* vs. Current *Ex-post* Incremental Load Impacts

Result	Previous *Ex-ante*, Incremental	Current *Ex-post*
# SAIDs	71,380	69,788
Reference (MW)	464	864
Load Impact (MW)	10.6	23.4
Per-SAID reference (kW)	6.5	12.4
Per-SAID load impact (kW)	0.15	0.34
% Load Impact	2.3%	2.7%

8.4 Current ex-post versus current ex-ante

Table 8.6 compares the *ex-post* and *ex-ante* load impacts from this study. Both results are taken from the August peak day. The *ex-ante* load impacts use 2017 forecast enrollments, assume utility-specific 1-in-2 weather conditions, and include only "incremental" load impacts (*i.e.*, those that will result from transitioning customers in the future).

Table 8.6 *Ex-post* vs. Incremental *Ex-ante* Load Impacts

Result	Current *Ex-post*	Current *Ex-ante*, Incremental
# SAIDs	69,788	70,563
Reference (MW)	864	561
Load Impact (MW)	23.4	16.5
Per-SAID reference (kW)	12.4	7.95
Per-SAID load impact (kW)	0.34	0.23
% Load Impact	2.7%	2.9%

The *ex-ante* forecast is based on the *ex-post* load impacts, so the difference between the two sets of results is due to two factors: weather conditions and enrollments, specifically the larger share of *ex-post* customers in the medium size group. Table 8.7 compares the *ex-post* and *ex-ante* enrollments by customer group. The *ex-post* analysis includes a much smaller share of under 20 kW customers (55 percent versus 74 percent) which is made up for by much larger shares of medium-sized (34 percent versus 17 percent) and agricultural (12 percent versus 8 percent) customers. The effect of the change in the distribution of customers by group is to increase the average customer size and load impact in the *ex-post* analysis. The percentage load impact is similar across the two results (2.7 percent versus 2.8 percent).

Table 8.7 Enrollments by Customer Group, *Ex-post* vs. Incremental *Ex-ante*

Result Type	Customer Group	Current *Ex-post*	Current *Ex-ante*, Incremental
Number of SAIDs	Small (under 20kW)	38,091	52,426
	Medium (20 to 200 kW)	23,393	12,291
	Agricultural	8,304	5,846
	Total	69,788	70,563
Share of SAIDs	Small (under 20kW)	55%	74%
	Medium (20 to 200 kW)	34%	17%
	Agricultural	12%	8%

Table 8.8 compares key components of the two analyses. The enrollment differences described above are the primary drivers of differences between *ex-post* and incremental *ex-ante* reference loads and load impacts. Higher *ex-post* temperatures also contribute to higher *ex-post* load and impact levels, but the temperature difference is small relative to the enrollment differences.

Table 8.8: *Ex-post* versus *Ex-ante* Factors

Factor	*Ex-post*	*Ex-ante*	Expected Impact
Weather	91.6 degrees Fahrenheit during HE 14 to 18.	90.5 degrees Fahrenheit during HE 14 to 18 of a utility-specific 1-in-2 August peak day.	Hotter *ex-post* weather increases the reference load and load impact.
Enrollments	69,788 SAIDs.	70,563 SAIDs.	There are slightly more service accounts in the *ex-ante* load impacts (representing higher customer transitions relative to the *ex-post* analysis), but the customers are much more likely to be in the under 20kW group (55% in the *ex-post* vs. 74% in *ex-ante*). Also, the *ex-ante* includes only 5,846 Ag accounts, whereas 8,304 were in the *ex-post* study.
Methodology	Group-level aggregated regressions using the natural log of average customer loads as the dependent variable.	Group-level aggregated regressions using the natural log of average customer loads as the dependent variable.	No effect. The *ex-post* models required to develop the various scenarios are also applied to the *ex-ante* study.

9. Recommendations

In the absence of a viable control group, methods for estimating TOU load impacts for newly transitioned customers are limited. Future studies will likely depend on within-treatment comparisons of loads before and after TOU migration, similar to the approach employed in this study. In order to enhance those results, we recommend that PG&E continue to collect and analyze interval data for previously transitioned customers (*e.g.*, accounts included in the PY 2014 and PY 2015 studies). An examination of usage patterns across several years for older TOU cohorts may provide insights regarding exogenous factors affecting future load impact estimates or TOU persistence.

Appendices

The following Appendices accompany this report. Appendix A describes the results of our model validation process. The additional appendices are Excel files that can produce the tables required by the Protocols.

Appendix A. Model Selection and Validity Assessment

A.1 Model Specification Tests

A range of model specifications were tested before arriving at the model used in the *ex-post* load impact analysis. The basic structure of the model is shown in Section 3.3. The tests are conducted using average-customer data by customer group (small, medium, and agricultural) and season (summer and winter).

The model variations are based on different methods of characterizing weather conditions. We tested 22 different combinations of weather variables in the summer and 12 specifications in the winter. The weather variables include: heat index (HI)[30], temperature-humidity index (THI)[31], cooling and heating degree hours (CDH and HDH, respectively)[32], cooling and heating degree days (CDD and HDD, respectively)[33], and the average temperature for the first 17 hours of a given day (MEAN17). These core variables may also be included as current hour, 3- or 24-hour moving averages, or lagged terms, and the degree day and degree hour variables are calculated using either a 60 or 65 degree threshold. A list of the 22 summer and 12 winter combinations of these variables that we tested is provided in Table A.1.

[30] HI = $c_1 + c_2T + c_3R + c_4TR + c_5T^2 + c_6R^2 + c_7T^2R + c_8TR^2 + c_9T^2R^2 + c_{10}T^3 + c_{11}R^3 + c_{12}T^3R + c_{13}TR^3 + c_{14}T^3R^2 + c_{15}T^2R^3 + c_{16}T^3R^3$, where T = ambient dry-bulb temperature in degrees Fahrenheit and R = relative humidity (where 10 percent is expressed as "10"). The values for the various *c*'s may be found here: http://en.wikipedia.org/wiki/Heat_index.

[31] THI = T – 0.55 x (1 – HUM) x (T – 58) if T>=58 or THI = T if T<58, where T = ambient dry-bulb temperature in degrees Fahrenheit and HUM = relative humidity (where 10 percent is expressed as "0.10").

[32] Cooling degree hours (CDH) was defined as MAX[0, Temperature – Threshold], where Temperature is the hourly temperature in degrees Fahrenheit and Threshold is either 60 or 65 degrees Fahrenheit. Customer-specific CDH values are calculated using data from the most appropriate weather station.

[33] Cooling degree days (CDD) are defined as MAX[0, (Max Temp + Min Temp) / 2 – Threshold], 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.

Table A.1: Weather Variables Included in Specification Search

Model Number	Summer	Winter
1	THI	CDH60, HDH60
2	HI	CDH65, HDH65
3	CDH60	CDH60, CDH60_24MA, HDH60, HDH60_24MA
4	CDH65	CDH65, CDH65_24MA, HDH65, HDH65_24MA
5	CDH60_3MA	CDH60, CDD60, HDH60, HDD60
6	CDH65_3MA	CDH65, CDD65, HDH65, HDD65
7	THI, THI_24MA	CDH60, LagCDD60, HDH60, LagHDD60
8	HI, HI_24MA	CDH65, LagCDD65, HDH65, LagHDD65
9	CDH60, CDH60_24MA	MEAN17
10	CDH65, CDH65_24MA	MEAN17, CDH60, HDH60
11	CDH60_3MA, CDH60_24MA	MEAN17, CDH65, HDH65
12	CDH65_3MA, CDH65_24MA	CDD60, HDD60
13	THI, LagCDD60	
14	HI, LagCDD60	
15	CDH60, LagCDD60	
16	CDH65, LagCDD60	
17	CDH60_3MA, LagCDD60	
18	CDH65_3MA, LagCDD60	
19	MEAN17	
20	CDH60, MEAN17	
21	CDH65, MEAN17	
22	CDD60, HDD60	

The model variations are evaluated according to their ability to predict usage on randomly selected test days from the pre-treatment (2014) period. The use of withheld test days allows us to test model performance against known “reference loads,” or actual customer usage on those days. We estimate the model excluding one of the test days and use the estimates to make out-of-sample predictions of customer loads on that day. The process is repeated for all of the test days. The model fit (*i.e.*, the difference between the actual and predicted loads on the test days, during afternoon hours in which events are typically called) is evaluated using mean absolute percentage error (MAPE) as a measure of accuracy, and mean percentage error (MPE) as a measure of bias.

As a robustness check, the testing procedure described above is also performed on a different set of test days in each season.

A.1.1 Selection of Event-Like Non-Event Days

Because the TOU rates included in this study are not event-based, we randomly select test days to withhold.[34] We perform the same tests using a different set of test days in each season to look for variations in model performance. Table A.2 contains a list of ten test days for summer and winter seasons.

Table A.2: List of Summer and Winter Test Days

Summer Weekdays	Winter Weekdays
5/15/2014	1/3/2014
6/2/2014	1/17/2014
7/1/2014	1/20/2014
7/31/2014	2/3/2014
8/13/2014	2/13/2014
8/15/2014	2/26/2014
8/19/2014	3/5/2014
8/29/2014	3/14/2014
9/8/2014	4/4/2014
9/22/2014	4/21/2014

A.1.2 Results from Tests of Alternative Weather Specifications

As described above, we tested 22 different sets of weather variables in the summer and 12 sets in the winter for each of three customer groups. Each model excludes one test day from the estimation and uses the estimated parameters to predict usage for that day. The MPE and MAPE are calculated across the part-peak windows (hours-ending 9 to 22) of the withheld days.

Table A.3 shows the adjusted R-squared, mean percentage error (MPE), and mean absolute percentage error (MAPE) for each specification and each size group during the summer season. The "winning" specification, based on results from the model validation exercise using *both* sets of withheld test days, is highlighted.[35] The adjusted R-squared values are uniformly high (in excess of 0.98) and vary little across the specifications tested, especially within size group. The bias (measured using MPE) tends to be positive for small and agricultural customers, indicating a tendency for the model to overstate true loads. However, the bias results are negative for the medium size group. The biases are generally small for all customer groups (usually below one percent). Model error, as measured by MAPE, ranges from 1.1 percent to 4.1 percent across the customer groups. Like the biases, the error rates do not display much variation across the alternative specifications.

[34] For event-based rates, we would select event-like non-event days based on weather conditions to withhold as test days.

[35] The highlighted specifications performed well across both sets of test days and preference was given to specifications that performed well for both small and medium customer groups.

Table A.3: Summer Specification Test Results by Customer Group

	Small			Medium			Agriculture		
Specification	Adj. R-squared	MPE	MAPE	Adj. R-squared	MPE	MAPE	Adj. R-squared	MPE	MAPE
1	0.998	-0.4%	1.8%	0.997	-0.9%	1.5%	0.987	0.4%	4.1%
2	0.997	-0.3%	2.1%	0.997	-0.8%	1.8%	0.987	0.5%	4.1%
3	0.998	-0.3%	1.6%	0.998	-0.8%	1.3%	0.988	0.5%	3.8%
4	0.998	-0.4%	1.7%	0.998	-0.7%	1.3%	0.988	0.5%	3.9%
5	0.998	-0.3%	1.8%	0.997	-0.7%	1.4%	0.988	0.5%	3.6%
6	0.998	-0.4%	1.8%	0.997	-0.7%	1.4%	0.988	0.4%	3.7%
7	0.998	0.0%	1.6%	0.998	-0.6%	1.3%	0.988	0.7%	4.0%
8	0.997	0.4%	1.6%	0.997	-0.3%	1.3%	0.987	0.9%	3.8%
9	0.998	0.4%	1.7%	0.998	-0.2%	1.1%	0.988	0.9%	3.7%
10	0.998	0.4%	1.8%	0.998	-0.2%	1.1%	0.988	0.9%	3.8%
11	0.998	0.3%	1.8%	0.997	-0.2%	1.3%	0.988	1.0%	3.6%
12	0.998	0.3%	1.8%	0.997	-0.2%	1.3%	0.988	0.9%	3.7%
13	0.998	0.2%	1.6%	0.997	-0.4%	1.3%	0.988	0.9%	3.9%
14	0.997	0.6%	1.8%	0.997	0.0%	1.5%	0.987	1.0%	3.8%
15	0.998	0.5%	1.7%	0.998	-0.1%	1.1%	0.989	1.1%	3.8%
16	0.998	0.5%	1.7%	0.998	0.0%	1.1%	0.989	1.1%	3.9%
17	0.998	0.4%	1.7%	0.997	-0.1%	1.3%	0.989	1.1%	3.7%
18	0.998	0.5%	1.7%	0.997	0.0%	1.3%	0.989	1.1%	3.7%
19	0.997	0.1%	1.9%	0.996	-0.4%	1.5%	0.986	0.7%	3.6%
20	0.998	0.0%	1.8%	0.998	-0.6%	1.2%	0.988	0.6%	3.9%
21	0.998	-0.1%	1.7%	0.998	-0.5%	1.2%	0.988	0.7%	3.9%
22	0.998	0.1%	1.8%	0.997	-0.3%	1.5%	0.986	0.8%	3.9%

Similar to Table A.3, Table A.4 shows the adjusted R-squared, mean percentage error (MPE), and mean absolute percentage error (MAPE) for each specification and each size group during the winter season.[36] The "winning" specification, based on results from the model validation exercise using *both* sets of withheld test days, is highlighted. Again, all specifications performed well with adjusted R-squared values greater than 0.98, MPE values less than or around one percent, and MAPE values less than 2.5 percent.[37]

[36] Recall that the Agricultural customer group was not analyzed during the winter season.

[37] The specifications chosen for each customer group and season include the following weather variables:

Small and Medium Summer – CDH65, MEAN17

Agricultural Summer – CDH60, CDH60_24MA, HDH60, HDH60_24MA

Small and Medium Winter – MEAN17, CDH65, HDH65

Table A.4: Winter Specification Test Results by Customer Group

	Small			Medium		
Specification	Adj. R-squared	MPE	MAPE	Adj. R-squared	MPE	MAPE
1	0.990	0.7%	2.4%	0.993	1.2%	2.2%
2	0.993	0.5%	2.3%	0.995	1.1%	2.0%
3	0.994	0.4%	2.1%	0.996	0.8%	1.8%
4	0.995	0.4%	2.1%	0.997	0.8%	1.8%
5	0.995	0.5%	1.9%	0.997	0.9%	1.7%
6	0.994	0.5%	1.8%	0.997	0.8%	1.7%
7	0.992	0.7%	2.4%	0.995	1.0%	2.1%
8	0.993	0.4%	2.3%	0.996	0.9%	2.0%
9	0.988	0.6%	2.4%	0.993	0.4%	2.1%
10	0.994	0.3%	2.0%	0.996	0.7%	1.7%
11	0.995	0.3%	1.8%	0.997	0.7%	1.7%
12	0.994	0.6%	2.2%	0.996	0.8%	1.8%

Figures A.1 through A.5 show actual hourly load levels for the average test day for each customer size group and season and the predicted load levels using the appropriate “winning” specification. In each case, actual and predicted load levels are very similar.

Figure A.1: Average Actual and Predicted Loads, Summer, Small

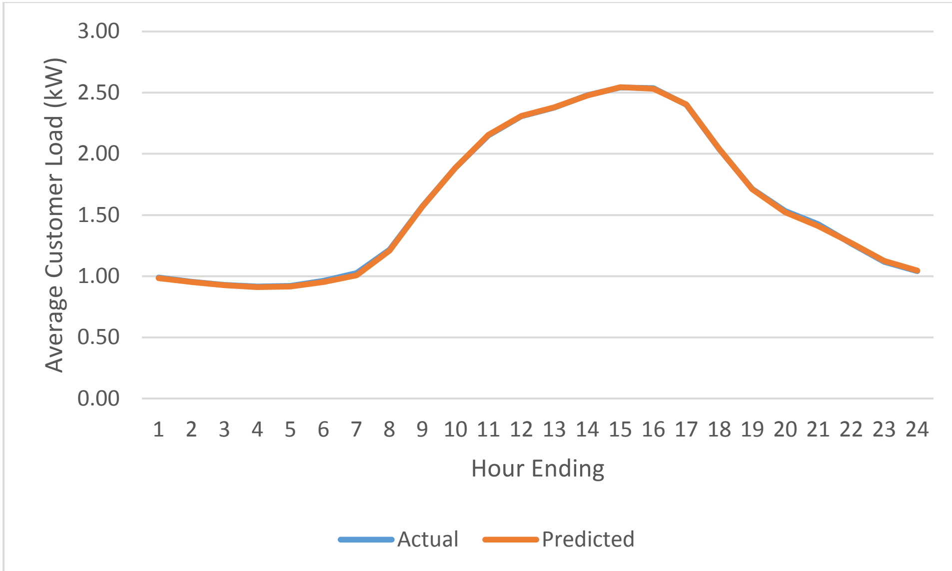


Figure A.2: Average Actual and Predicted Loads, Summer, Medium

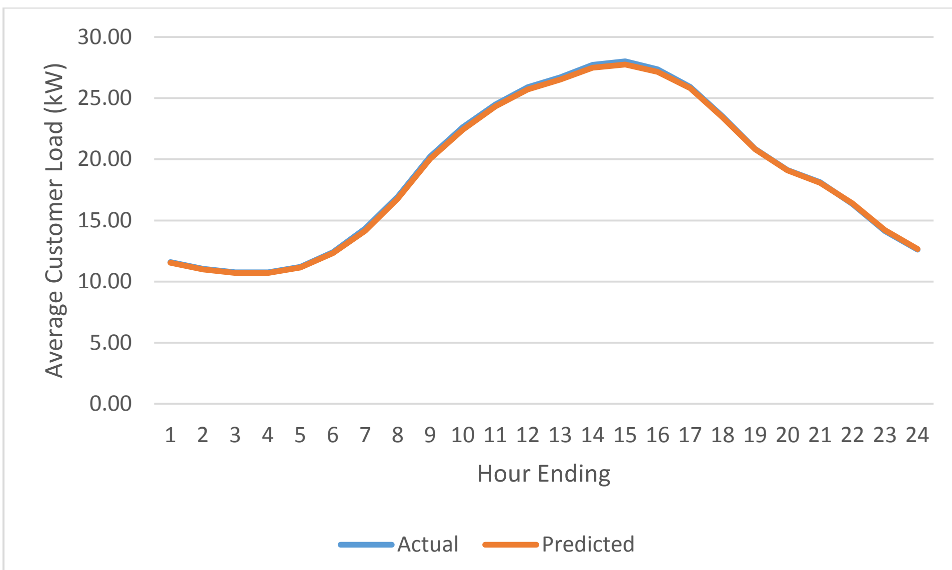


Figure A.3: Average Actual and Predicted Loads, Summer, Agriculture

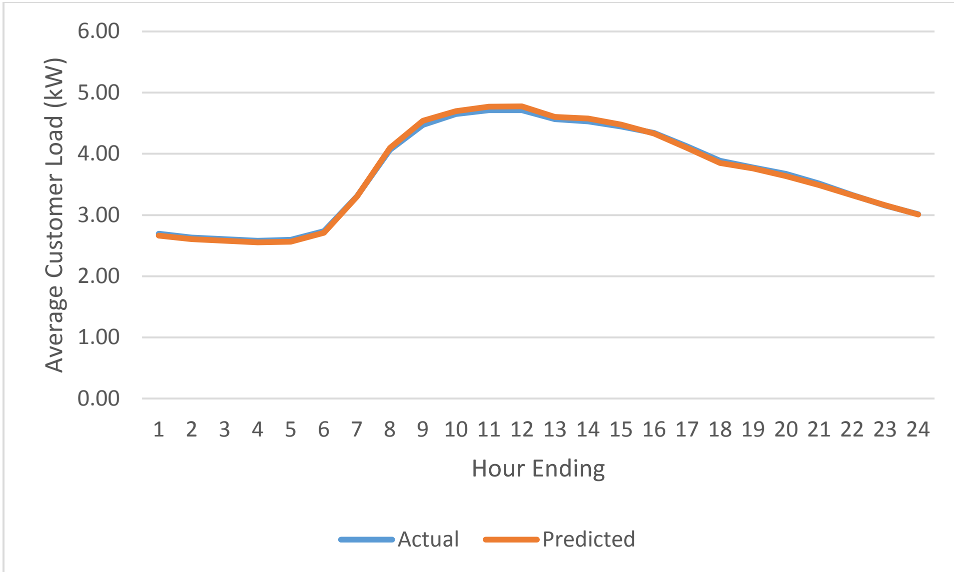


Figure A.4: Average Actual and Predicted Loads, Winter, Small

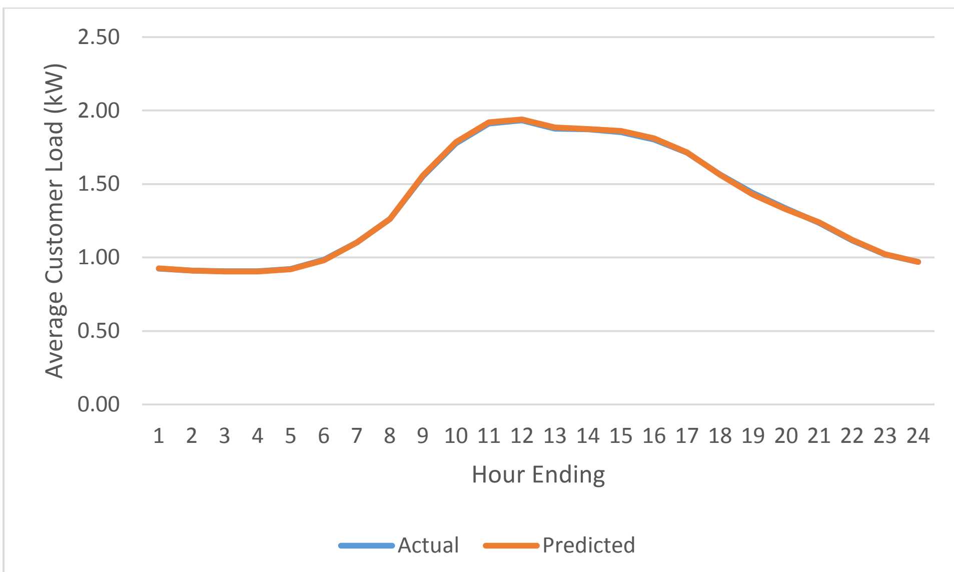
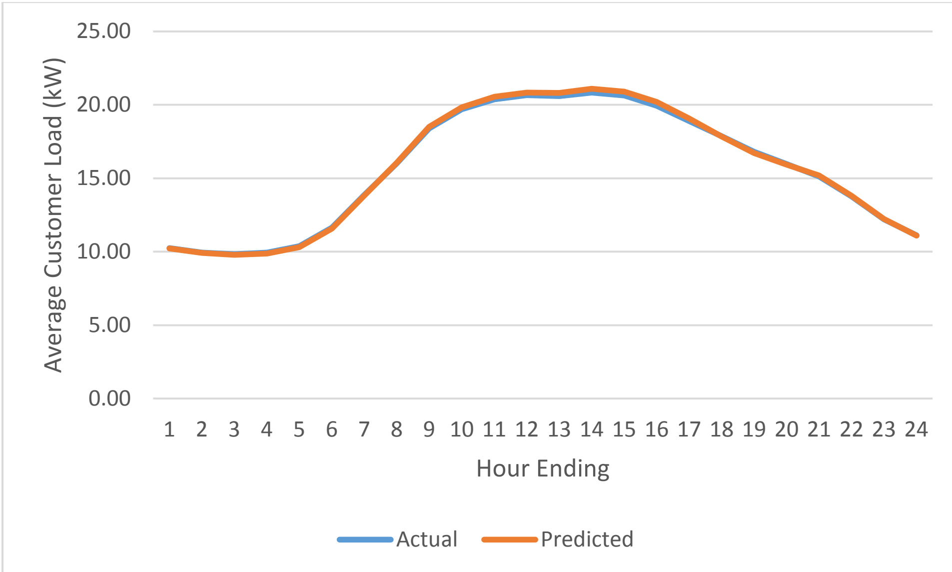


Figure A.5: Average Actual and Predicted Loads, Winter, Medium



Additional Appendices

The following Appendices accompany this report as Excel files that produce the tables required by the Protocols.

Study Appendix B	PG&E Non-Residential TOU *Ex-post* Load Impact Protocol Tables
Study Appendix C	PG&E Non-Residential TOU *Incremental Ex-ante* Load Impact Protocol Tables
Study Appendix D	PG&E Non-Residential TOU *Embedded Ex-ante* Load Impact Protocol Tables