2014 Load Impact Evaluation of Pacific Gas and Electric Company's Mandatory Time-of-Use Rates for Small and Medium Non-residential Customers: *Ex-post* and *Ex-ante* Report

CALMAC Study ID PGE0354

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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 and medium-sized non-residential customers in 2014. The report provides: 1) estimates of *ex-post* load impacts for customers who newly transitioned to TOU rates prior to 2014 and an *ex-ante* forecast of load impacts for 2015 through 2025 that is based on the IOU'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. The TOU rates under each tariff, which apply to customer accounts that have been transitioned to TOU, are seasonal three-tier rates, with energy prices that differ by summer and non-summer 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 104,000 in November 2013. Similarly, cohorts of 17,500 agricultural customer accounts were transitioned in March of 2013. The planned transition of 15,500 in 2014 did not occur due to an error. The remaining SMB and agricultural customers will be transitioned in 2014, 2015, and 2016. The availability of some remaining customers on existing non-TOU rates allows the potential to select useful comparison groups to assist in the evaluation of demand and energy impacts for those customers who have been transitioned. The *ex-pos*t study presented here concerns the customers transitioned in November 2013.

We estimate *ex-post* load impacts by comparing load data for treatment (TOU) customers and a comparable control group consisting of non-TOU customers, for time periods prior to and after the treatment customers were enrolled in the TOU rate, using a difference-in-differences evaluation approach.

We follow an approach that is similar to the one used in the PY 2013 evaluation of load impacts for these customer classes, with some modifications, as described below. An overview of the approach is that it includes the following activities:

- We select random samples from the customers in the two relevant rate classes (*i.e.*, A-1 and A-10—agricultural customers were not transitioned in March 2014) who were newly transitioned to TOU rates in November 2013;
- Using propensity score matching, we select sets of comparable control-group customers from the set of customers who remain on non-TOU rates;
- We conduct various forms of difference-in-differences analyses to estimate TOU load impacts by hour or TOU pricing period. The methods for calculating the load impacts include simple statistical comparisons and fixed-effects panel regressions.

Our *ex-post* load impact estimates show load reductions in response to TOU rates for both customer groups and in all pricing periods ranging from 1.6 to 3.7 percent. This pattern of demand response 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.

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 customer TOU enrollments for SMB customers is approximately 63,000 in early 2015 (following the transition of customers in November 2014) and increase to approximately 161,000 by August 2016 (due to two transitions of agricultural customers and an additional transition of SMB customer). August peak day incremental TOU load impacts are approximately 10 MW in 2015 rising to approximately 23 MW by 2025.

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 317,926 service accounts in our embedded TOU load impact forecast. Of these, 82,871 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 250 to 300 MW in summer months and are approximately 50 MW in non-summer 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 and medium-sized non-residential customers in 2014. The report provides: 1) estimates of *ex-post* load impacts for customers who newly transitioned to TOU rates prior to 2014 and an *ex-ante* forecast of load impacts for 2015 through 2025 that is based on the IOU'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 2013?
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 2015 through 2025?

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. The TOU rates under each tariff, which apply to customer accounts that have been transitioned to TOU, are seasonal three-tier rates, with energy prices that differ by summer and non-summer 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 104,000 in November 2013. Similarly, cohorts of 17,500 agricultural customer accounts were transitioned in March of 2013. The planned transition of 15,500 in 2014 did not occur due to an error. The remaining SMB and agricultural customers will be transitioned in 2014, 2015, and 2016. The availability of some remaining customers on existing non-TOU rates allows the potential to select useful comparison groups to assist in the evaluation of demand and energy impacts for those customers who have been transitioned. The *ex-pos*t study presented here concerns the customers transitioned in November 2013.

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 this study, the availability of customers who have not yet been transitioned to a TOU rate provides a pool of customers from which a comparable control group may be selected. In addition, the availability of hourly interval data for a time period prior to the 2014 cohort's transition to TOU rates allows a comparison of their usage prior to and following their transition.

Given these conditions, we estimate *ex-post* load impacts by comparing load data for treatment (TOU) customers and a comparable control group consisting of non-TOU customers, for time periods prior to and after the treatment customers were enrolled in the TOU rate, using a difference-in-differences evaluation approach.

We follow an approach that is similar to the one used in the PY 2013 evaluation of load impacts for these customer classes, with some modifications, as described below. An overview of the approach is that it includes the following activities:

- We select random samples from the customers in the two relevant rate classes (*i.e.*, A-1 and A-10—agricultural customers were not transitioned in March 2014) who were newly transitioned to TOU rates in November 2013;
- Using propensity score matching, we select sets of comparable control-group customers from the set of customers who remain on non-TOU rates;
- We conduct various forms of difference-in-differences analyses to estimate TOU load impacts by hour or TOU pricing period. The methods for calculating the load impacts include simple statistical comparisons and fixed-effects panel regressions.

One difference between this study and the PY2013 study is 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

Table ES.1 summarizes the load impacts by pricing period and customer group. The analyses estimates load reductions in response to TOU rates for both customer groups and in all pricing periods. This pattern of demand response 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.[1]

[1] Note that the estimated load impacts for the medium business customers are not robust with respect to the propensity score matching methodology, as described in Appendix B.

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

TOU Pricing Period			% Load Change: Small Business (Under 20kW)	% Load Change: Medium Business (20-200kW)
Summer	Weekdays	Peak	-2.1%	-2.4%
		Part-Peak	-2.5%	-2.3%
		Off-Peak	-2.1%	-2.6%
	Weekends & Holidays	Off-Peak	-1.9%	-2.4%
Non-Summer	Weekdays	Part-Peak	-1.9%	-3.5%
		Off-Peak	-1.6%	-3.7%
	Weekends & Holidays	Off-Peak	-1.6%	-3.7%

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

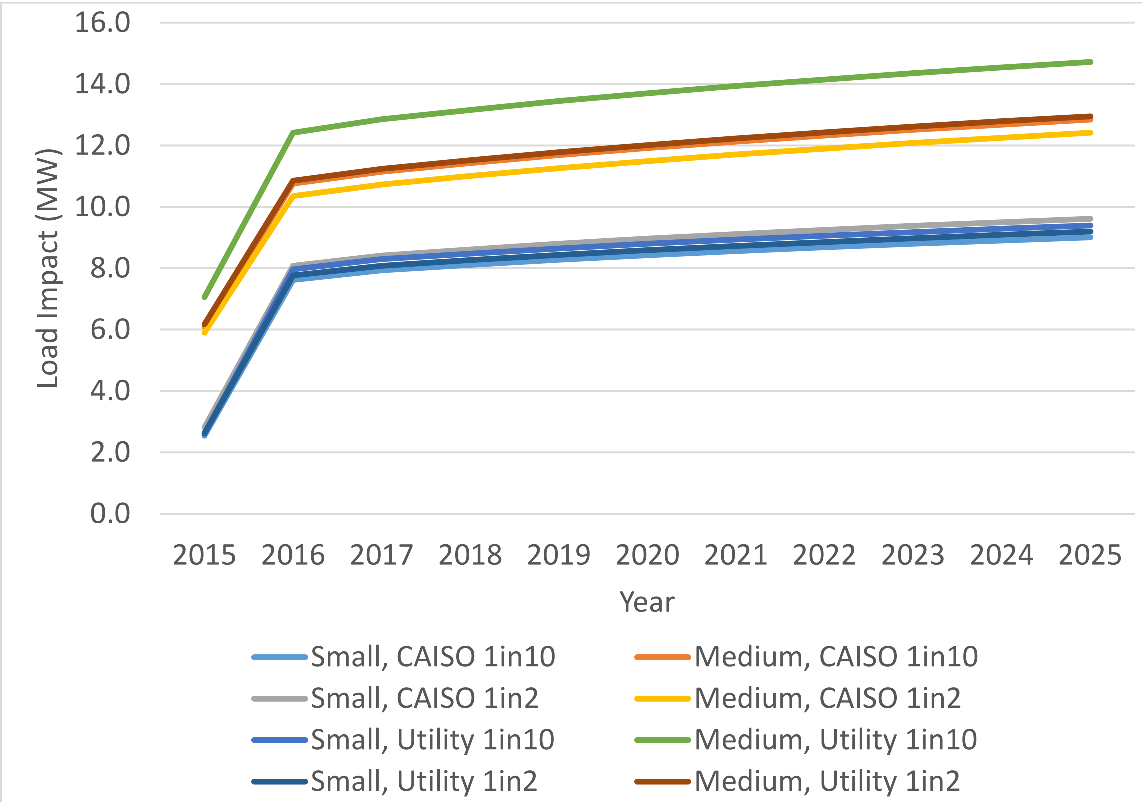
There are three sources of incremental TOU load impacts in the forecast period:

- Transitions of SMB customers in November 2014 and November 2015;
- Transitions of agricultural customers in March 2015 and March 2016; 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 2014 *ex-post* load impacts associated with customers transitioned in November 2013. For agricultural customers, we use the 2013 *ex-post* load impacts estimated for customers transitioned in March 2013.

Incremental customer TOU enrollments for SMB customers is approximately 63,000 in early 2015 (following the transition of customers in November 2014) and increase to approximately 161,000 by August 2016 (due to two transitions of agricultural customers and an additional transition of SMB customer). Figure ES.1 shows the incremental load impact for each August in the forecast period, for each customer group and weather scenario.

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.

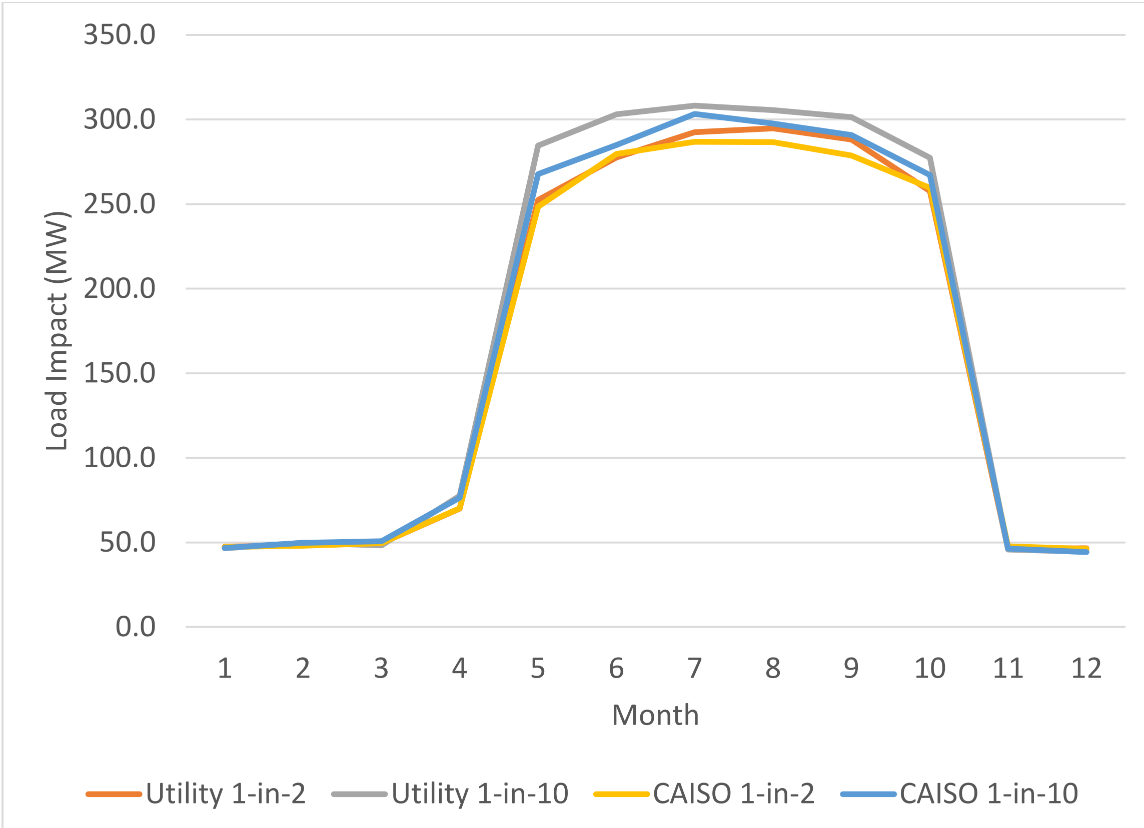
For the customers who have been on TOU rates for many years, we cannot estimate *ex-post* load impacts because these customers have not been observed on non-TOU rates. Therefore, load impacts for these customers have been simulated using existing studies of TOU demand response. For consistency across studies, we have carried forward the analysis of these customers from the previous study (conducted following the 2013 program year). However, 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 this analysis and also added scenarios that correspond to CAISO-coincident conditions. (The updated weather scenarios correspond to utility-specific 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 2013. The methods follow those used to develop the incremental TOU load impact forecast described in Section 6.1, but applying a different set of enrollments.

There are 317,926 service accounts in our embedded TOU load impact forecast. Of these, 82,871 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 250 to 300 MW and non-summer load impacts are approximately 50 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 and medium-sized non-residential customers in 2014. The report provides: 1) estimates of *ex-post* load impacts for customers who newly transitioned to TOU rates prior to 2014 and an *ex-ante* forecast of load impacts for 2015 through 2025 that is based on the IOU'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 2013?
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 2015 through 2025?

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; Section 4 contains the detailed *ex-post* load impact results for *small* commercial and industrial customers transitioned in late 2013; Section 5 contains the detailed *ex-post* load impact results for *medium-sized* commercial and industrial customers transitioned in late 2013; Section 6 describes the *ex-ante* load impact forecast; Section 7 contains descriptions of differences in various scenarios of *ex-post* and *ex-ante* load impacts; and Section 8 provides recommendations. Appendix A contains an assessment of the validity of the study.

2. Description of the Rates and Transition Process

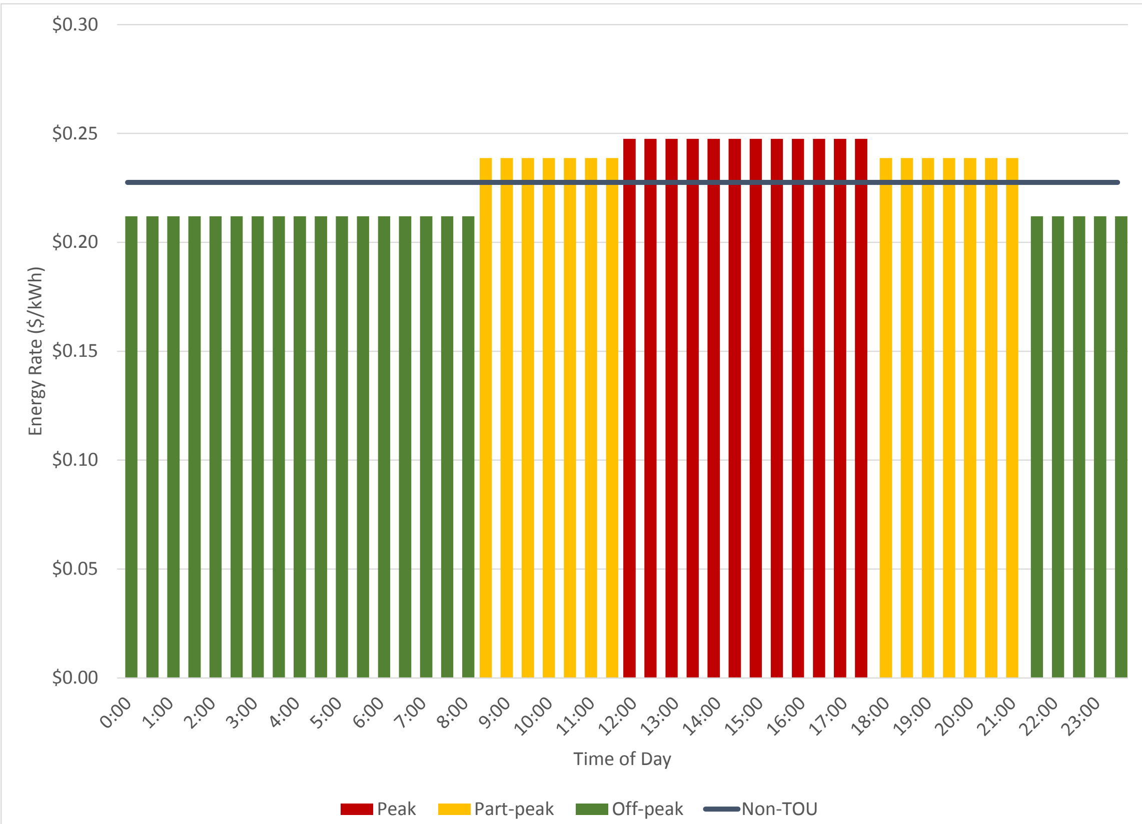
This section provides details on the relevant non-residential TOU rates and the process used to transition customers to those rates. The primary portion of this study focuses on small and medium business customers, which PG&E defines as customer accounts with maximum demands of less than 20 kW (small) 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 agricultural customers under the AG-1 rate are also being transitioned to TOU rates (*e.g.*, AG-4), but no new customers were transitioned in 2014.

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. The TOU rates under each tariff, which apply to customer accounts that have been transitioned to TOU, are seasonal three-tier rates, with energy prices that differ by summer and non-summer and by peak, part-peak, and off-peak time periods.

Figure 2.1 illustrates the TOU and non-TOU energy prices ($/kWh) that apply in summer months for the A-1 tariff (the non-summer 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: 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 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

[2] Prices effective on May 1, 2014 per Cal. P.U.C. Sheet No.33732-E.

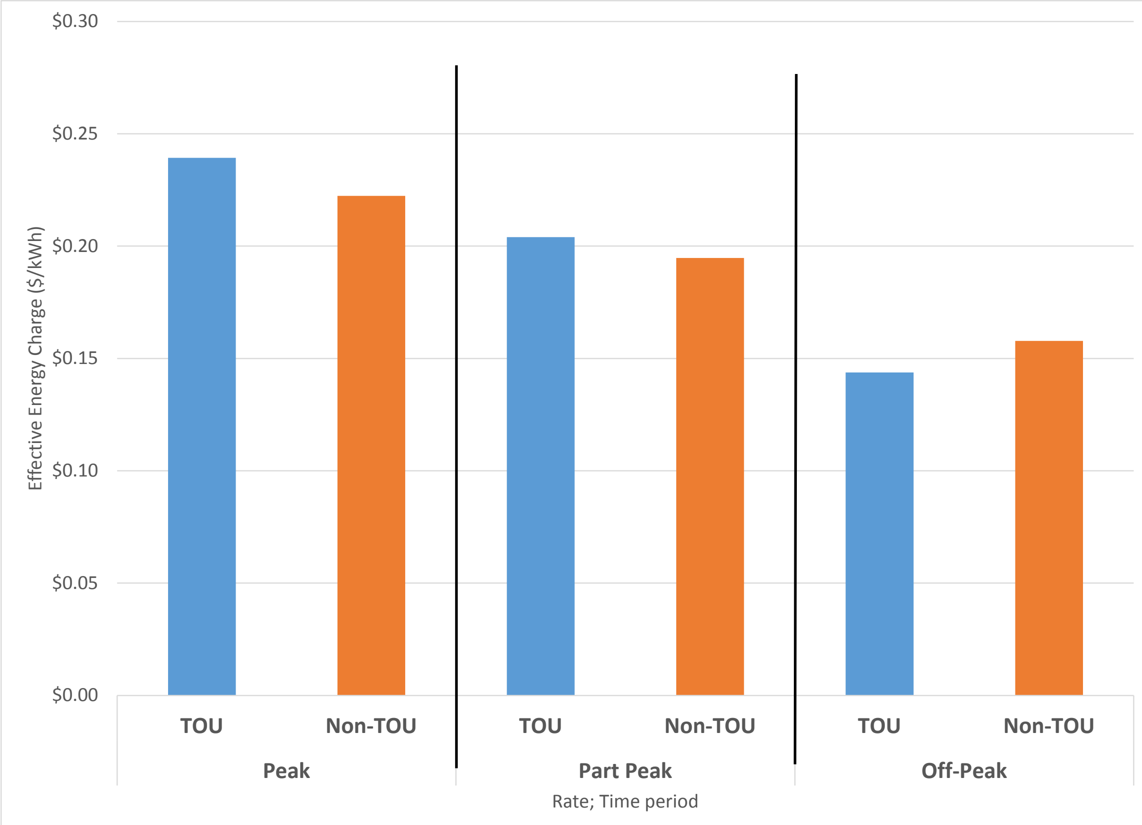
[3] The same demand charges are applied under non-TOU and TOU versions of the A-10 tariff. Demand charges vary by voltage level. The secondary voltage demand charge is $13.87 per kW in the summer period and $6.46 in the winter period (per Cal. P.U.C. Sheet No.33737-E, effective May 1, 2014).

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).

Figure 2.2: 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. However, since load impacts for those rates are not examined in the primary portion of this study, we do not provide details on the rates.

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 104,000 in November 2013. Similarly, cohorts of 17,500 agricultural customer accounts were transitioned in March of 2013. The planned transition of 15,500 in 2014 did not occur due to an error. The remaining SMB and agricultural customers will be transitioned in 2014, 2015, and 2016.[4] The availability of some remaining customers on existing non-TOU rates allows the potential to select useful comparison groups to assist in the evaluation of demand and energy impacts for those customers who have been transitioned.

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:

[4] Approximately 62,000 SMB customers transitioned to TOU rates in November 2014.

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).[5]

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 2014.

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 this study, the availability of customers who have not yet been transitioned to a TOU rate provides a pool of customers from which a comparable control group may be selected. In addition, the availability of hourly interval data for a time period prior to the 2014 cohort's transition to TOU rates allows a comparison of their usage prior to and following their transition.

Given these conditions, we estimate *ex-post* load impacts by comparing load data for treatment (TOU) customers and a comparable control group consisting of non-TOU customers, for time periods prior to and after the treatment customers were enrolled in the TOU rate, using a difference-in-differences evaluation approach.

We follow an approach that is similar to the one used in the PY 2013 evaluation of load impacts for these customer classes, with some modifications, as described below. An overview of the approach is that it includes the following activities:

- We select random samples from the customers in the two relevant rate classes (*i.e*., A-1 and A-10—agricultural customers were not transitioned in March 2014) who were newly transitioned to TOU rates in November 2013;
- Using propensity score matching, we select sets of comparable control-group customers from the set of customers who remain on non-TOU rates;

[5] 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 conduct various forms of difference-in-differences analyses to estimate TOU load impacts by hour or TOU pricing period. The methods for calculating the load impacts include simple statistical comparisons and fixed-effects panel regressions.

One difference between this study and the PY2013 study is 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 relatively large number of SMB customer accounts migrated in November 2013 provides a large pool of customers from which to draw a treatment group for use in the PY 2014 study. Given the need to report results for a number of different customer characteristics (*e.g.*, business type, location, and size), we selected a relatively large sample of 10,000 small-sized customers and used 7,442 medium-sized customers who transitioned in November 2013 and had suitable data available.

To select the treatment and control-group samples, we requested databases of customer characteristics, monthly billing data statistics, and interval load data for the relevant pre-TOU period. We selected comparable control-group customers for the treatment groups (*i.e.*, small and medium business) from the numbers of customers who remained on the existing non-TOU rates during 2014.

Each sampled treatment customer was matched to an eligible control-group customer using propensity score (PS) matching. To implement PS matching, we first estimate a logit regression in which the dependent variable is an indicator (zero / one) variable for whether the customer was transitioned to the TOU rate in November 2013 (*i.e.*, TOU customers are coded as one and control customers are coded as zero). The explanatory variables include customer characteristics drawn from the pre-TOU period (*i.e*., 2013). The characteristics include industry group indicator variables, weather station indicator variables, and a range of usage characteristics across periods of the day and months of the year.

The predicted values from this logit model, called *propensity scores*, are then compared across treatment and eligible control customers. We selected the "nearest neighbor" for each treatment customer, subject to the score difference falling within a pre-specified range, which helps ensure higher quality matches. We allowed eligible control customers to be matched to as many as ten treatment customers, with weights employed throughout the analysis to ensure that we appropriately reflect the multiple matches.

3.2 Estimation of demand and energy impacts

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

1. We begin by calculating *simple statistical comparisons* for various customer sub-groups to illustrate differences in the observed usage data for the treatment and control groups. For example, we calculate average summer peak-period usage in the pre- and post-TOU periods for the treatment and control groups. Differences in pre-TOU peak usage indicate potential differences in the make-up of the samples. Differences in post-TOU peak usage provide an initial estimate of the overall TOU impact, while a comparison of the two sets of differences provides a difference-in-differences estimate of the TOU impact, which controls for any pre-TOU differences in the two groups. We produce these estimates for each customer class.
2. A limitation on the simple statistical comparisons is that they average across all available days and customers, and thus do not account for the effects of factors such as weather conditions. Accounting for the effects of these factors requires a formal regression analysis using observations, for example, on peak-period usage for each weekday in the available pre-TOU and post-TOU periods, for each customer account in the treatment and control group samples. 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; whether the observation is in the pre- or post-TOU period; whether the customer is a treatment or control-group customer; and whether the observation is in the post-TOU period for a treatment group customer. Weather variables indicate weather conditions on each observed day. The estimated coefficient on the interacted variable for post-TOU period and treatment group represents a difference-in-differences estimate of the peak-period usage effect of participation in the TOU rate.[6] Hour-specific models are estimated to conform to the Protocol requirements.
3. While the above approach describes the model used to estimate our primary results (the hourly load impacts for SMB customers), a second regression approach is used to develop all of the scenarios required to meet the Protocols (*e.g.*, typical weekday and peak day by month). This method is an *aggregate* version of the above approach, which averages the hourly usage observations across customers in the treatment and control groups. The dependent variable is the difference between the average treatment and control loads 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 also produces difference-in-differences

[6] The weather variable may also be interacted with the indicator of treatment group in the post-TOU period to estimate the weather sensitivity of the TOU load impacts.

estimates of TOU load impacts, but facilitates the estimation of the effect of weather on TOU load impacts by interacting weather variables with the TOU treatment indicator variable.

In all of the above analyses, TOU load impacts are estimated for summer and winter seasons, and by pricing period (*e.g.,* peak, partial-peak, and off-peak) or hour. The third analysis method is used to develop results 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).

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

For the primary method (the second method above), separate models are estimated for the summer (May through September in 2013 and 2014) and non-summer seasons (January through April in 2013 and 2014), for weekdays and weekends within each of those seasons, and for each hour of the day.[7] The regression equation is defined as follows:

$$Q^h_{t,c} = a + b^h_{Post} \times Post_t + b^h_{Post\_Treat} \times (Post_t \times Treat_{t,c}) + b^h_{CDD} \times CDD_{t,c} + b^h_{HDD} \times HDD_{t,c}$$

$$+ \sum_i (b^h_{DTYPEi} \times DTYPE_{i,t}) + \sum_i (b_i^{MONTH\_YR} \times MONTH\_YR_{i,t}) + u_c + e_{t,c}$$

Table 3.1: 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
$Treat_{t,c}$	a dummy variable for treatment (TOU) customers
$CDD_{t,c}$	cooling degree days on date *t* for customer *c*
$HDD_{t,c}$	heating degree days 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 *h* superscripts indicate that we estimate hour-specific models. The *Post* variable is equal to one for all customers (treatment and control) following the TOU transition (2014 in this case) and zero before the transition. The *Treat* variable is equal to one for those customers who were transitioned to TOU rates and zero for the control-group

[7] October 2014 data were not available when the study commenced. We do not use October through December 2013 data because we do not have corresponding 2014 data and because we want to avoid incorporating data during the TOU transition period.

customers. The cooling and heating degree variables account for each customer's weather conditions on each day.[8] The interaction between the Post and Treat variables provides the difference-in-differences estimate of the TOU load response during the hour in question.

Separate models are estimated for the medium and small business customer groups; for weekends and weekdays; summer and non-summer; and each hour of the day (for 192 distinct models). Each model includes all of the treatment and control-group customers within a given customer class, where the control-group customers are weighted according to how many times each was matched to a treatment customer.

Because of the large number of models (and numbers of customers within each model), we developed similar models (the third approach described above) using aggregated loads for the various required sub-groups (*e.g.*, by LCA) that include an estimate of the effect of weather on TOU impacts. This is accomplished by interacting the *Post* x *Treat* interaction variable with the *CDD* and *HDD* variables. In these models, the dependent variable is the difference between average treatment and average control-group loads during the hour in question. The CDD and HDD variables are load-weighted averages across the included customers.[9]

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. In the case of *ex-post* load impacts, the parameters that constitute the load impact estimates (the *Post* x *Treat* interaction variables) are not estimated with certainty. We base the uncertainty-adjusted load impacts on the variances associated with these coefficients. Specifically, the uncertainty-adjusted scenarios were simulated under the assumption that each hour's load impact is normally distributed with the mean equal to the estimated load impact and the standard deviation equal to the standard error associated with the load impact estimate. Results for the 10^{th}, 30^{th}, 70^{th}, and 90^{th} percentile scenarios are generated from these distributions. Hourly uncertainty-adjusted load impacts are produced using standard errors from the hourly models, while the averages by pricing period are produced using standard errors from period-specific models (estimated after averaging across the hours within the pricing period).

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[8] CDD = MAX(Average of the Max and Min Daily Temperatures in degrees Fahrenheit – 60, 0)
HDD = MAX(60 – Average of the Max and Min Daily Temperatures in degrees Fahrenheit, 0)

[9] These aggregated models can be estimated for the required sub-groups or for the entire size group. The estimates and forecasts from the group-level model will not necessarily match those obtained by adding across the sub-group models. The group-level model both averages across more customer data than each sub-group model (potentially producing more "reliable" results) and uses a more restrictive model specification (*i.e.*, it applies one set of estimated coefficients to the group-level load, whereas the sub-group models each have their own set of estimated coefficient). The sub-group models are particularly helpful for obtaining the *ex-ante* forecast, as they allow us to reflect a changing distribution of service accounts across LCAs over time (whereas the group-level model reflects the distribution of customers contained in the estimation sample). The distinction is less important when estimating *ex-post* load impacts because the group-level estimation sample reflects the population of interest.

4. Small Business Customer Study Findings

In order to analyze the effect of TOU rates on small (maximum demands below 20 kW) business customer usage patterns, we first compile a set of eligible treatment and control customers. We use propensity score matching to select control customers with pre-TOU characteristics comparable to those of treatment customers and then compare pre- and post-TOU loads using difference-in-differences models.

4.1 Propensity Score Matching Results

The eligible treatment group consists of 80,000 customers who transitioned to TOU rates in November 2013, from which we draw a random sample of 10,000 accounts. After applying screens to ensure the quality of data, we are left with 9,944 treatment customers.

The eligible control group consists of 38,000 small business customers who remain on non-TOU rates throughout the analysis period (January 2013 to September 2014). Again, after applying data quality screens, there are 17,000 remaining control customers for use in propensity score matching.

As described in Section 3.1, the propensity score (PS) matching algorithm uses a set of explanatory variables from the pre-TOU period (*i.e.*, 2013) to select control customers that are most comparable to the treatment customers.[10] The set of explanatory variables include customer-specific indicators for industry groups, weather stations, and a series of usage characteristics across periods of the day and months of the year. We allow each eligible control customer to serve as the matched control for up to ten different treatment customers, and we require the match to be of a specified quality in order to be considered successful. Table 4.1 summarizes the number of customers included in PS matching and those that are successfully matched.

Table 4.1: Small Business Numbers of Treatment and Control Group Matches

Customer Group	# Eligible for Matching	# of Successful Matches
Treatment	9,944	9,783
Control	17,097	5,835

Through PS matching, we identify 5,835 control customers with geographic, industry, and usage characteristics suitably comparable to 9,783 treatment customers. Sixty-three percent of the control customers are matched to just one treatment customer, 22 percent are matched to two treatment customers, and the remaining are matched to up

[10] Only small (below 20 kW) businesses are included in the treatment and eligible control customer groups. Matching is performed in cohorts according to more granular size definitions. There are nine size cohorts for small businesses. A small business control customer is only matched to a treatment customer if the difference between their propensity scores is within 0.01.

to ten treatment customers. The quality of the matches can be assessed by comparing distributions of treatment and matched control customers by geographic region and industrial classification.[11]

Figure 4.1 illustrates geographic comparability by showing the distribution of treatment customers (outer pie slices) and matched control customers (inner pie slices) by weather station. Each weather station is similarly represented in both the treatment and matched control groups. For both groups, the most common weather station is Potrero (15 percent), followed by Santa Maria (11 percent), Santa Cruz, Salinas, Fresno, and Milpitas (6 percent each).

Figure 4.1: Small Business Matches by Weather Station

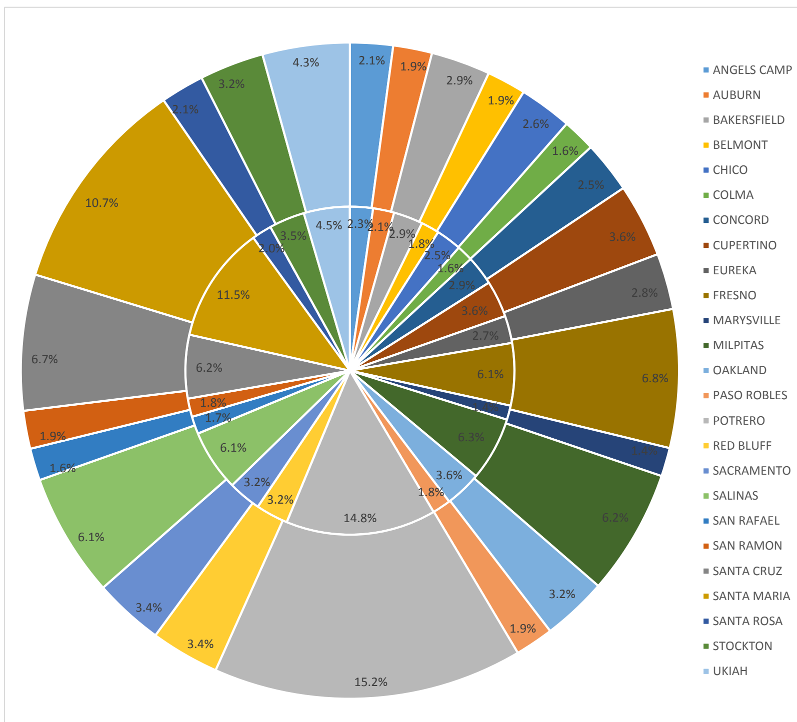
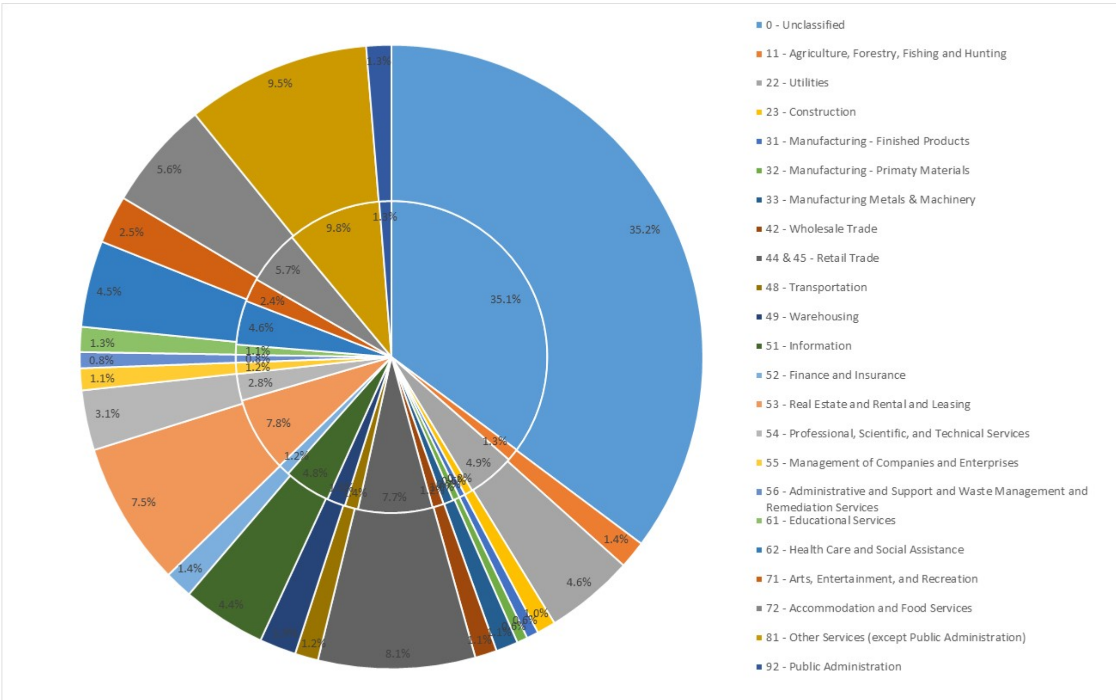


Figure 4.2 illustrates the distribution of treatment (outer pie slices) and control (inner pie slices) customers by industrial classification (2-digit NAICS codes). Again, the distributions are similar, with roughly equal shares of treatment and matched control customers in each industry group. Approximately 35 percent of customers in both groups fall into the "Unclassified" category, either indicating that an industry code was not provided or that fewer than 100 small businesses in the entire available population were identified in that industry group. The next most common industries were Other

[11] Appendix A contains detailed comparisons and formal tests of the statistical significance of the differences between matched treatment and control customers on the bases of usage levels, usage patterns, geography, and industry.

Services (10 percent), Real Estate and Leasing (8 percent), Retail Trade (5 percent), and Accommodation and Food Services (5 percent).

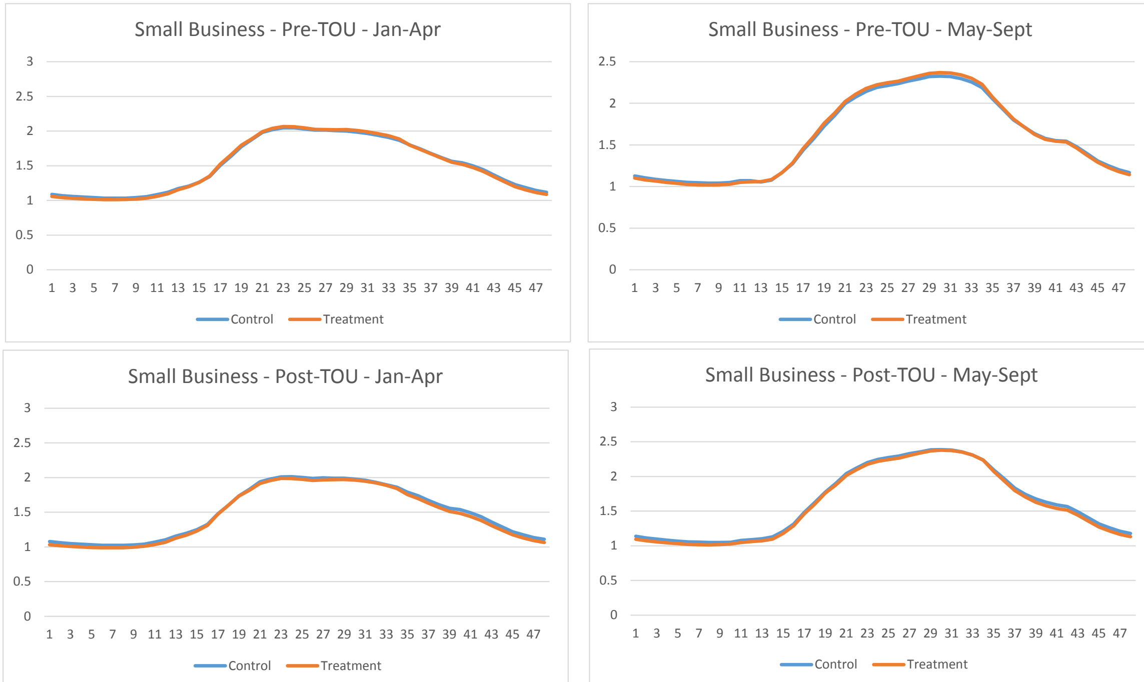
Figure 4.2: Small Business Matches by Industry Group



With successful PS matching, we also hope to see that average load profiles for treatment and control customers are similar in the pre-TOU period. The top two graphs in Figure 4.3 show average treatment and control load profiles for non-summer and summer months in 2013, respectively.[12] Average control customer loads are represented by the solid blue line, and treatment loads are represented by the dashed orange line. The y-axis is measured in kW, and the x-axis is measured in 30-minute increments. The treatment and control load profiles are well-aligned, with a correlation coefficient of 0.999 in both the summer and non-summer periods. Minor differences in load shapes are present, with control loads being slightly higher than treatment loads in the morning and evening hours, and treatment loads being slightly higher than those for control customers in the afternoon.

[12] October, November, and December are not included in any part of the analysis, because these months are most likely to be affected by the November 2013 transition of customers to TOU rates. The summer period covers May-October (September, in the analysis), as described by the TOU tariff, and all other months make up the non-summer period.

Figure 4.3: Small Business Treatment/Control Load Profile Comparisons



The bottom two graphs in Figure 4.3 show average load profiles for treatment and matched control customers in the post-TOU period (2014) during non-summer and summer months, respectively. The load profiles are still well-aligned, although control customer loads exceed treatment customer loads in all but one 30-minute period in each of the non-summer and summer periods. This can serve as an informal confirmation of our expectation that loads will be reduced in response to TOU rates, particularly in the afternoon (peak) period.

4.2 Estimation Results

As described in Section 3.1, we conduct several analyses to estimate TOU demand and energy impacts. The first analysis is a simple statistical comparison of differences between treatment and control customer average usage during pre-TOU and post-TOU periods, or difference-in-differences. For this analysis, we divide the day into TOU pricing periods. For example, the summer weekday peak period represents average kWh usage during the hours from noon to 6 p.m., when TOU rates are highest. Please refer to Section 2.1 for details regarding TOU rate periods.

Table 4.2 contains values used to calculate the impact of TOU rates on average usage during various parts of the day. The first set of three columns are associated with the pre-TOU period (2013) and contain average treatment (TOU) customer usage, average matched control customer usage, and the difference (treatment-control) between the two, respectively. The second set of three columns shows comparable values for the post-TOU (2014) period. The second to last column contains the results of the difference-in-differences calculation (post-TOU difference-pre-TOU difference), and the last column contains the difference-in-differences values expressed as percentages of implied post-TOU treatment customer reference loads.

Table 4.2: Small Business Simple Difference-in-Differences Statistics

Rate Type	Day Type	Period	Pre-TOU Transition			Post-TOU Transition			Impact (kW)	% Impact
			TOU	Control	Diff.	TOU	Control	Diff.		
Summer	Weekdays	Peak	2.28	2.24	0.04	2.28	2.30	-0.02	-0.05	-2.2%
		Part Peak	1.80	1.78	0.01	1.79	1.83	-0.04	-0.05	-2.6%
		Off Peak	1.13	1.14	-0.01	1.13	1.16	-0.04	-0.02	-1.9%
	Weekends & Holidays	Off-Peak	1.33	1.34	0.00	1.31	1.34	-0.03	-0.02	-1.7%
Non-Summer	Weekdays	Part Peak	1.84	1.83	0.01	1.79	1.81	-0.03	-0.03	-1.9%
		Off Peak	1.12	1.14	-0.02	1.10	1.13	-0.04	-0.02	-1.4%
	Weekends & Holidays	Off Peak	1.12	1.14	-0.02	1.10	1.13	-0.04	-0.02	-1.4%

Table 4.2 shows that TOU rates lead to energy reductions in all periods in both the summer and non-summer seasons. The largest reduction, 2.6 percent, occurs during summer part-peak hours, with slightly smaller reductions during summer peak hours of 2.2 percent. Both of these reductions are larger than those calculated for off-peak summer hours (1.9 percent on weekdays and 1.7 percent on weekends).

The load impacts are not entirely consistent with our expectations from 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.[13]

As discussed in Section 3.1, the limitation of the simple difference-in-differences calculations shown in Table 4.2 is that they average across all available days and customers, and thus do not 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 a difference-in-differences 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.

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

Table 4.4 displays similar results for the non-summer period. All estimated coefficients used to calculate non-summer percent load impacts are also statistically significant with the exception of hour-ending 9 (8:00 to 9:00 a.m.) on non-summer weekends.

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	1.10	1.08	-2.0%	1.11	1.09	-1.7%
2	1.07	1.05	-2.2%	1.08	1.06	-2.2%
3	1.04	1.03	-1.6%	1.05	1.03	-2.1%
4	1.03	1.01	-1.8%	1.03	1.01	-2.1%
5	1.03	1.02	-0.9%	1.02	1.01	-1.3%
6	1.07	1.06	-1.3%	1.03	1.01	-1.6%
7	1.13	1.09	-3.3%	1.00	0.97	-2.7%
8	1.27	1.24	-2.7%	1.01	0.99	-1.9%
9	1.59	1.54	-3.0%	1.12	1.10	-2.0%
10	1.89	1.83	-2.9%	1.30	1.27	-1.8%
11	2.13	2.07	-2.7%	1.49	1.46	-2.0%
12	2.27	2.22	-2.6%	1.61	1.58	-1.8%
13	2.33	2.27	-2.6%	1.65	1.63	-1.5%
14	2.39	2.34	-2.2%	1.68	1.66	-1.3%
15	2.44	2.39	-2.0%	1.70	1.67	-1.4%
16	2.43	2.38	-1.9%	1.69	1.67	-1.6%
17	2.33	2.29	-1.8%	1.67	1.64	-1.9%
18	2.06	2.02	-2.0%	1.60	1.58	-1.6%
19	1.80	1.76	-2.2%	1.52	1.49	-1.5%
20	1.65	1.61	-2.4%	1.46	1.43	-2.6%
21	1.57	1.53	-2.8%	1.44	1.41	-2.5%
22	1.43	1.40	-2.2%	1.35	1.33	-1.8%
23	1.27	1.24	-2.2%	1.23	1.21	-1.9%
24	1.17	1.15	-2.1%	1.15	1.13	-1.9%
Averages						
Peak	2.33	2.28	-2.1%			
Part Peak	1.82	1.77	-2.5%			
Off Peak	1.16	1.14	-2.1%	1.33	1.31	-1.9%

Table 4.4: Small Business Estimated Load Impacts from Hourly Regression – Non-Summer

Hour	Weekday Reference kWh	Weekday Observed kWh	Weekday % Load Impact	Weekend Reference kWh	Weekend Observed kWh	Weekend % Load Impact
1	1.05	1.03	-1.9%	1.06	1.04	-2.1%
2	1.02	1.00	-1.8%	1.03	1.01	-1.9%
3	1.01	0.99	-1.8%	0.99	0.97	-2.0%
4	1.01	0.99	-1.7%	1.01	0.99	-2.1%
5	1.02	1.00	-1.5%	1.01	0.99	-2.0%
6	1.07	1.05	-1.4%	1.03	1.01	-1.6%
7	1.17	1.15	-1.7%	1.04	1.03	-1.1%
8	1.29	1.27	-1.5%	1.02	1.01	-0.9%
9	1.57	1.55	-1.2%	1.08	1.08	-0.5%
10	1.81	1.79	-1.3%	1.23	1.22	-0.5%
11	1.99	1.95	-1.8%	1.39	1.37	-1.6%
12	2.04	2.00	-2.0%	1.46	1.43	-1.7%
13	2.02	1.98	-2.1%	1.46	1.43	-1.9%
14	2.02	1.98	-2.0%	1.44	1.42	-1.7%
15	2.02	1.98	-2.0%	1.43	1.41	-1.7%
16	1.98	1.95	-1.8%	1.41	1.39	-1.5%
17	1.91	1.88	-1.8%	1.39	1.37	-1.4%
18	1.77	1.74	-1.8%	1.41	1.39	-1.4%
19	1.64	1.60	-2.0%	1.40	1.38	-1.8%
20	1.53	1.50	-2.1%	1.37	1.34	-2.1%
21	1.44	1.41	-2.0%	1.33	1.30	-2.0%
22	1.30	1.28	-2.1%	1.24	1.21	-2.2%
23	1.17	1.15	-1.4%	1.14	1.12	-1.8%
24	1.10	1.08	-1.7%	1.08	1.06	-1.7%
Averages						
Peak						
Part Peak	1.81	1.77	-1.9%			
Off Peak	1.13	1.11	-1.6%	1.23	1.21	-1.6%

The average values at the bottom of Tables 4.3 and 4.4 represent average hourly load impacts for each TOU pricing period. These can be compared to those from the simple difference-in-differences calculations presented in the far right column of Table 4.2. During both the summer and non-summer seasons, average percent load impacts are very similar across the two analyses, and the pattern across peak, part-peak, and off-peak periods is the same. That is, all periods experience post-TOU load reductions, and in the summer season part-peak hours have the largest percent load reductions. Table 4.5 summarizes the load impacts calculated or estimated by both methods in all relevant periods.

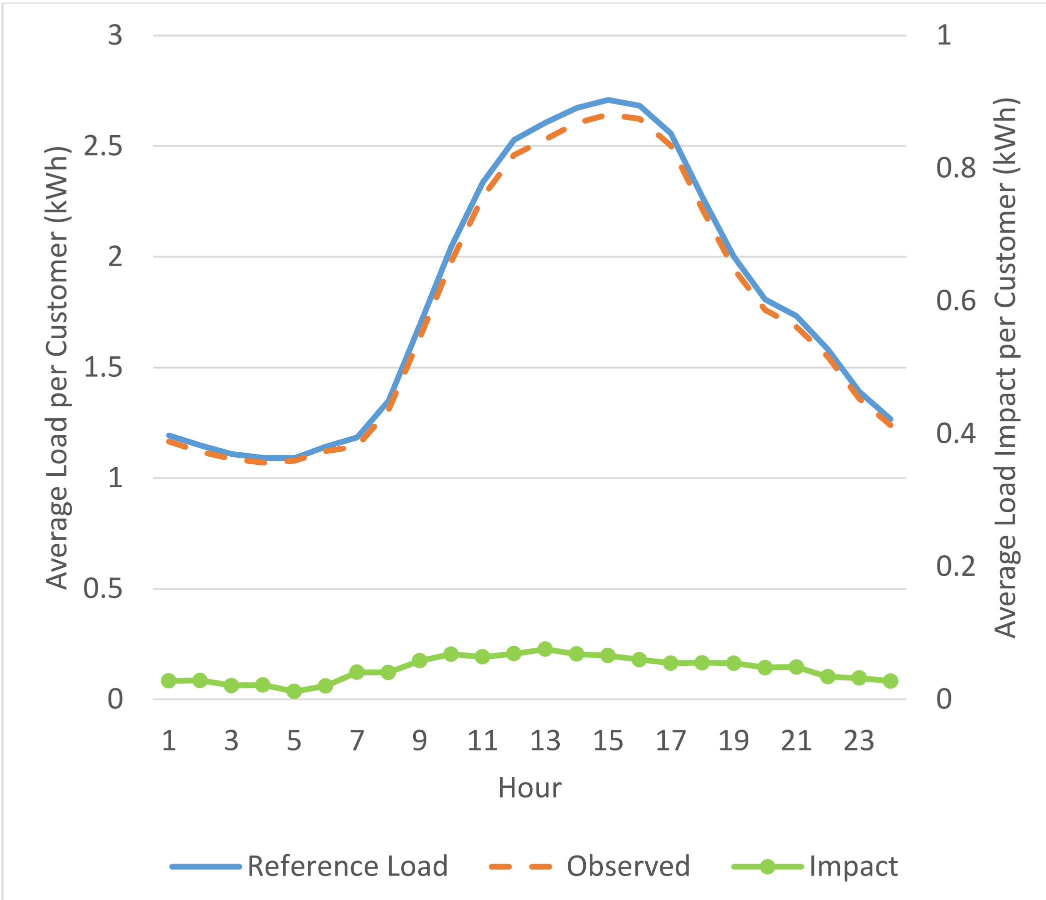
Table 4.5: Small Business Comparison of Estimated and Calculated Load Impacts, Two Analysis Methods

TOU Pricing Period			% Impact: Simple Difference-in-Differences	% Impact: Fixed-Effects Regression
Summer	Weekdays	Peak	-2.2%	-2.1%
		Part-Peak	-2.6%	-2.5%
		Off-Peak	-1.9%	-2.1%
	Weekends & Holidays	Off-Peak	-1.7%	-1.9%
Non-Summer	Weekdays	Part-Peak	-1.9%	-1.9%
		Off-Peak	-1.4%	-1.6%
	Weekends & Holidays	Off-Peak	-1.4%	-1.6%

Load impact estimates presented thus far are derived from models that include all matched treatment and control small businesses. 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 treatment and control groups. The dependent variable is the difference between the average treatment and control loads 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 also produces difference-in-differences estimates of TOU load impacts, but facilitates the estimation of the effect of weather on TOU load impacts by interacting weather variables with the TOU treatment indicator variable.

Figure 4.4 illustrates average estimated reference loads, actual observed loads, and estimated load impacts on the 2014 August system peak day for all 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 implied average percent load impact during the peak period is -2.4 percent, which is again similar to but higher than those found in the previous analyses for peak periods during all summer weekdays. The same pattern that we found previously for part-peak and off-peak periods holds as well, with average part-peak load impacts of -2.8 percent and off-peak load impacts of 2.3 percent.

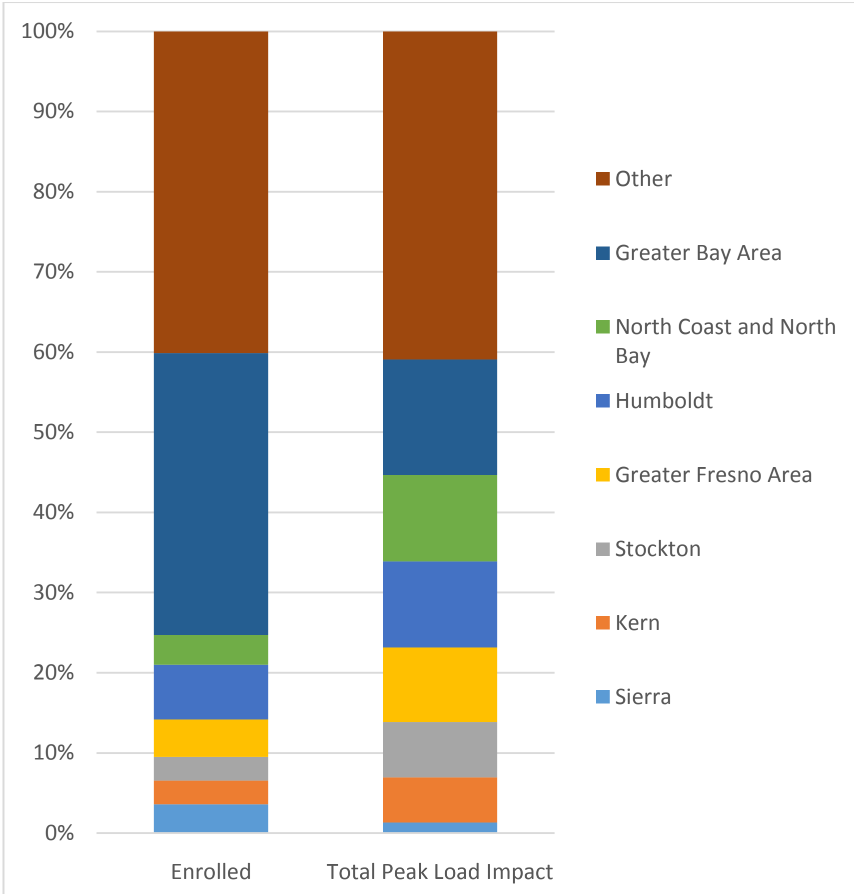
Figure 4.4: August System Peak Reference Loads and Load Impacts for All Small Businesses (Average Per Customers kWh)



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 2014 system peak day.

In Figure 4.5, the largest share of total load impacts and customers, 40 percent, comes from the "Other" LCA group. The Greater Bay Area contributes the next largest share of load reductions, 16 percent, but makes up 35 percent of the population. The disparity between load impacts and customers in the Greater Bay Area is made up for by the remaining LCAs, with each contributing more than their customer share to total load reductions.

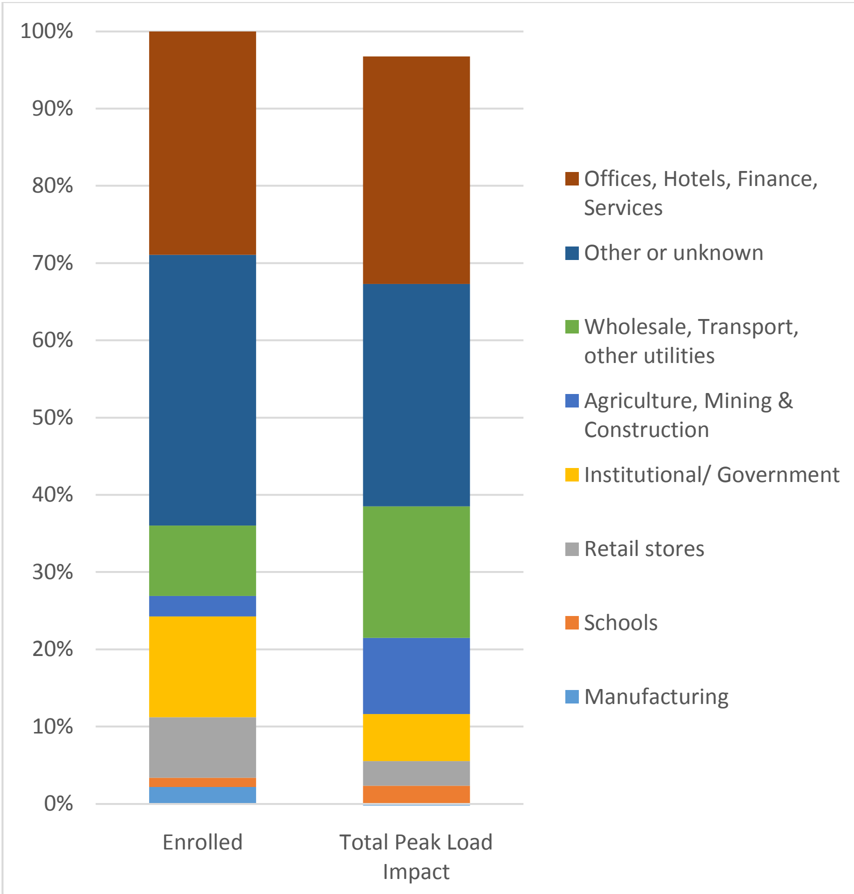
Figure 4.5: Small Business August System Peak Distribution of Load Impacts by LCA



In Figure 4.6, the top two industry groups contributing to total load reductions are "Other or Unknown" and "Offices, Hotels, Finance, Services", each with a 31 percent share, which is similar to their respective shares of the population. The "Manufacturing" sector experiences estimated load increases, which a negative contribution to load reductions (not presented in the graph).[14]

[14] Load increases were also estimated for the Manufacturing sector in the PY 2013 analysis.

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 (maximum demands between 20 to 200 kW) business customer energy usage is analyzed in a similar fashion as that described in Section 4 for small business customers.

5.1 Propensity Score Matching Results

The treatment group consists of approximately 7,500 medium business customers who transitioned to TOU rates in November 2013. After applying screens to ensure quality of the data, there are 7,402 treatment customers available for propensity score matching. The eligible control group consists of 18,000 medium size business customers who remain on non-TOU rates throughout the analysis period (January 2013 to September 2014). After applying data quality screens, there are 6,891 remaining control customers for use in propensity score matching.

As described in Section 3.1, the propensity score (PS) matching algorithm uses a set of explanatory variables from the pre-TOU period (*i.e.*, 2013) to select control customers that are most comparable to the treatment customers.[15] The set of explanatory variables include customer-specific indicators for industry groups, weather stations, and a series of usage characteristics across periods of the day and months of the year. We allow each eligible control customer to serve as the matched control for up to ten different treatment customers, and we require the match to be of a specified quality in order to be considered successful. Table 5.1 summarizes the number of customers included in PS matching and those that are successfully matched.

Table 5.1: Medium Business Treatment and Control Group Matches

Customer Group	# Eligible for Matching	# of Successful Matches
Treatment	7,402	7,235
Control	6,891	3,027

Through PS matching, we identify 3,027 control customers with geographic, industry, and usage characteristics suitably comparable to 7,235 treatment customers. 48 percent of the control customers are matched to just one treatment customer, 22 percent are matched to two treatment customers, and the remaining are matched to up to ten treatment customers.[16] The quality of the matches can be assessed by comparing distributions of treatment and matched control customers by geographic region and industrial classification.[17]

Figure 5.1 illustrates geographic comparability between matched treatment and control customers by showing the distribution of treatment customers (outer pie slices) and matched control customers (inner pie slices) by weather station. Each weather station is similarly represented in both the treatment and matched control groups. For both groups, the most common weather stations are Milpitas and Potrero (11 percent each), followed by Fresno (10 percent), and Stockton (7 percent).

[15] Only medium (between 20 and 199.99 kW) businesses are included in the treatment and eligible control customer groups. Matching is performed in cohorts according to more granular size definitions. There are five size cohorts for medium businesses. A medium business control customer is only matched to a treatment customer if the difference between their propensity scores is within 0.02.
[16] The percentage of control customers matched to more than one treatment customer is higher for medium businesses primarily due to the limited availability of candidates.
[17] Appendix A contains detailed comparisons and formal tests of the statistical significance of the differences between matched treatment and control customers on the bases of usage levels, usage patterns, geography, and industry.

Figure 5.1: Medium Business Matches by Weather Station

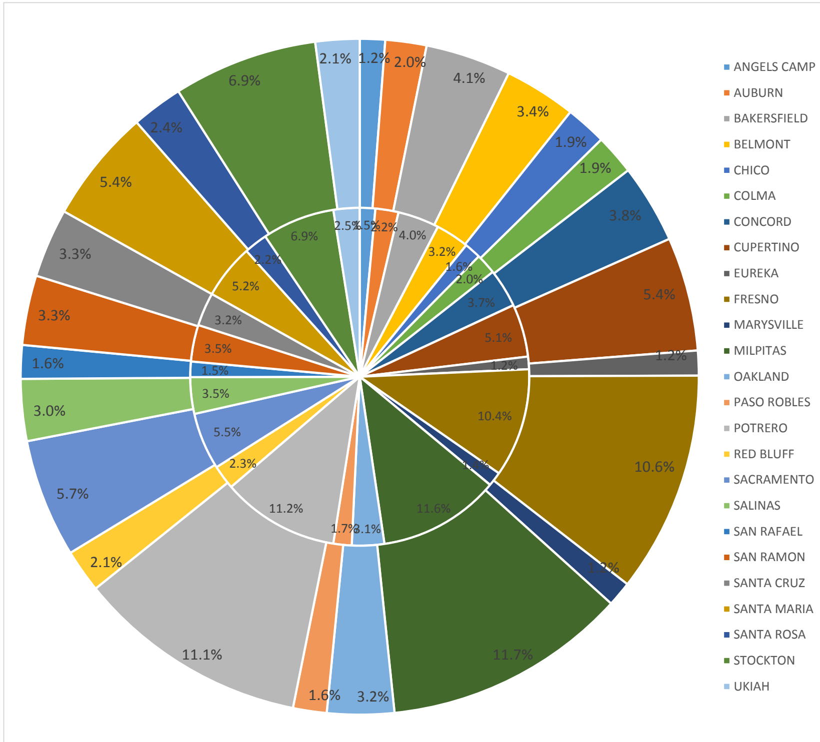
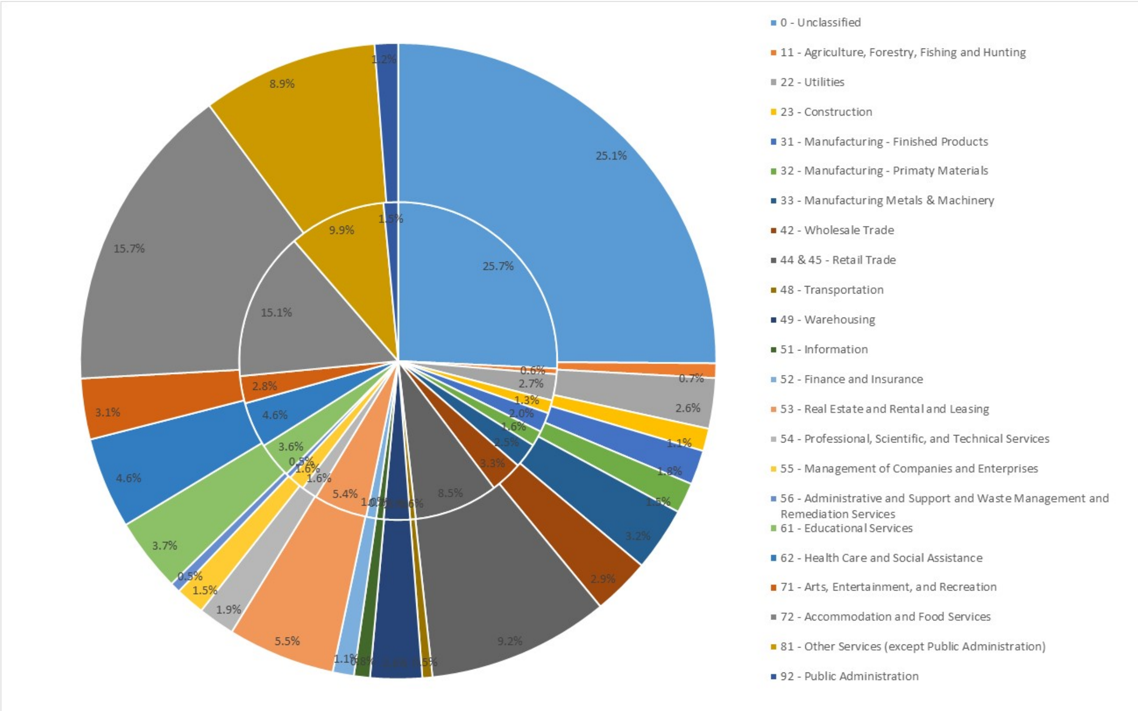


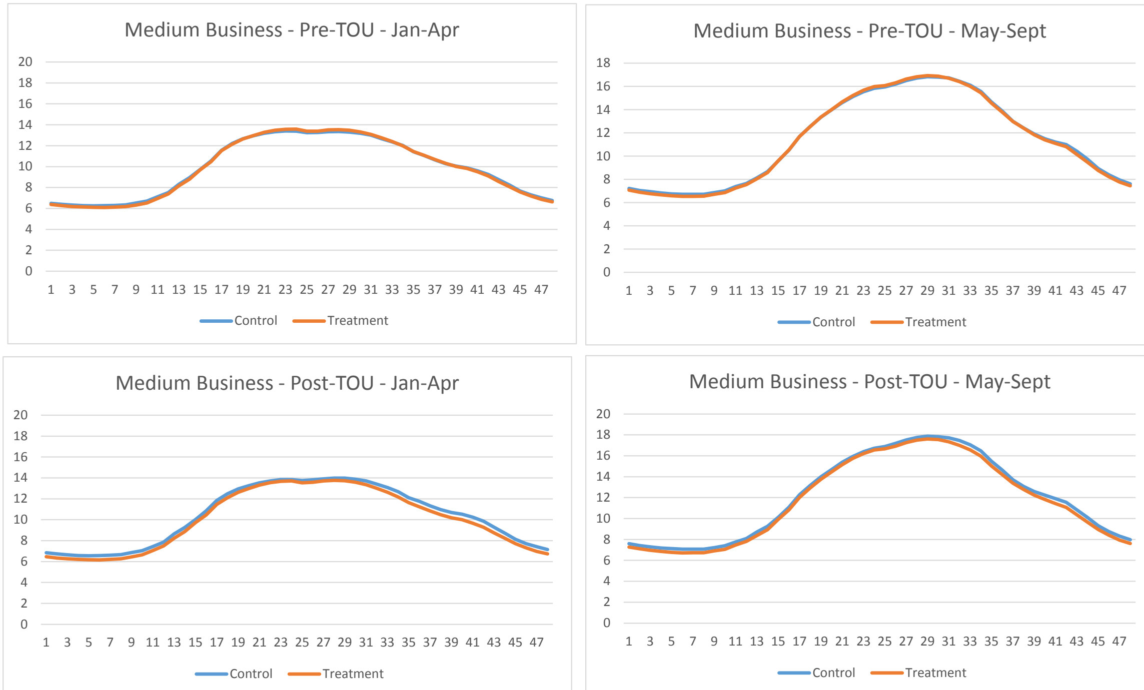
Figure 5.2 illustrates the distribution of treatment (outer pie slices) and control (inner pie slices) customers by industrial classification (2-digit NAICS codes). Again, the distributions are similar, with roughly equal shares of treatment and matched control customers in each industry group. Approximately 25 percent of customers in both groups fall into the “Unclassified” category, either indicating that an industry code was not provided or that fewer than 40 medium businesses in the entire available population were identified in that industry group. The next most common industries were Accommodation and Food Services (15 percent), Other Services (9 percent), and Retail Trade (7 percent).

Figure 5.2: Medium Business Matches by Industry Group



With successful PS matching, we also hope to see that average load profiles for treatment and control customers are similar in the pre-TOU period. The top two graphs in Figure 5.3 show average treatment and control load profiles for non-summer and summer months in 2013, respectively. Average control customer loads are represented by the solid blue line, and treatment loads are represented by the dashed orange line. The y-axis is measured in kW, and the x-axis is measured in 30-minute increments. Treatment and control load profiles are well-aligned, with a correlation coefficient of 0.999 in both the summer and non-summer periods. Minor differences in load shapes are present, with control loads being slightly higher than treatment loads in the morning and evening hours, and treatment loads being slightly higher than those for control customers in the afternoon.

Figure 5.3: Medium Business Treatment/Control Load Profile Comparisons



The bottom two graphs in Figure 5.3 show average load profiles for treatment and matched control customers in the post-TOU period (2014) during non-summer and summer months, respectively. Again, the load profiles are well-aligned, although control customer loads exceed treatment customer loads in all intervals of the non-summer and summer seasons. This can serve as an informal confirmation of our expectation that loads will be reduced in response to TOU rates, particularly in the afternoon (peak price) period.[18]

5.2 Estimation Results

As described in Section 3.1, we conduct several analyses to estimate TOU demand and energy impacts. The first analysis is a simple statistical comparison of differences between treatment and control customer average usage during pre-TOU and post-TOU

[18] It should be noted that the TOU load impact results for medium business are sensitive to the PS matching method employed. In one version of the PS matching algorithm (which differed only slightly from the method we ultimately chose), we found very strong matches in terms of weather station and industry distributions as well as pre-TOU load profiles, however the post-TOU load profiles implied modest load *increases* (about 1 percent) for treatment customers. In this sense, despite the strength of the matches presented above, the resulting load impact estimates are not robust to different, but seemingly valid, treatment and control group selections. While the method presented in this section is more intuitively appealing to us (in that it matches medium-sized customers only to other medium-sized customers, whereas the alternative method also allows them to be matched to small customers), the sensitivity of the results with respect to the matching method implies that some caution should be exercised when interpreting or applying the estimates for this customer group. See Appendix B for additional details.

periods, or difference-in-differences. For this analysis, we divide the day into TOU pricing periods. For example, the summer weekday peak period represents average kWh usage during the hours from noon to 6 p.m., when TOU rates are highest. Please refer to Section 2.1 for details regarding TOU rate periods.

Table 5.2 contains values used to calculate the impact of TOU rates on average usage during each TOU pricing period. The first set of three columns are associated with the pre-TOU period (2013) and contain average treatment (TOU) customer usage, average matched control customer usage, and the difference (treatment-control) between the two, respectively. The second set of three columns shows comparable values for the post-TOU (2014) period. The second to last column contains results of the difference-in-differences calculation (post-TOU difference-pre-TOU difference), and the last column contains the difference-in-differences values expressed as percentages of implied post-TOU treatment customer reference loads.

Table 5.2: Medium Business Simple Difference-in-Differences Statistics

Rate Type	Day Type	Period	Pre-TOU Transition			Post-TOU Transition			Impact (kW)	% Impact
			TOU	Control	Diff.	TOU	Control	Diff.		
Summer	Weekdays	Peak	16.16	16.15	0.01	16.76	17.12	-0.36	-0.37	-2.2%
		Part Peak	13.09	13.11	-0.02	13.52	13.82	-0.30	-0.28	-2.0%
		Off Peak	7.84	7.98	-0.13	8.07	8.40	-0.33	-0.19	-2.4%
	Weekends & Holidays	Off-Peak	9.07	9.09	-0.02	9.15	9.40	-0.24	-0.23	-2.4%
Non-Summer	Weekdays	Part Peak	12.12	12.07	0.05	12.27	12.64	-0.37	-0.41	-3.3%
		Off Peak	7.37	7.50	-0.13	7.44	7.84	-0.40	-0.27	-3.5%
	Weekends & Holidays	Off Peak	7.61	7.62	-0.01	7.69	8.00	-0.31	-0.30	-3.8%

Table 5.2 shows that TOU rates lead to energy reductions in all periods in both the summer and non-summer seasons. The largest summer reductions, 2.4 percent, occurs during summer off-peak hours, with slightly smaller reductions during summer peak hours, 2.2 percent, and summer part-peak hours 2.0 percent. The non-summer season had larger load reductions of greater than 3 percent in each period, but the pattern of highest reductions in off-peak hours holds. As was the case in the small customer analysis, the pattern of load response is more consistent with conservation than TOU demand response.

As discussed in Section 3.1, the limitation of simple difference-in-differences calculations as shown in Table 5.2 is that they average across all available days and customers, and thus do not 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 a difference-in-differences 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 percent load impacts is statistically significant at the 0.05 (95 percent confidence) level. Table 5.4 displays similar results for the non-summer period.

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

	Weekday			Weekend		
Hour	**Reference kWh**	**Observed kWh**	**% Load Impact**	**Reference kWh**	**Observed kWh**	**% Load Impact**
1	7.39	7.19	-2.7%	7.40	7.21	-2.6%
2	7.09	6.92	-2.4%	7.06	6.87	-2.6%
3	6.95	6.75	-2.9%	6.83	6.64	-2.8%
4	6.93	6.73	-2.8%	6.73	6.54	-2.9%
5	7.19	6.99	-2.7%	6.79	6.59	-2.8%
6	7.86	7.67	-2.5%	6.92	6.76	-2.2%
7	8.98	8.70	-3.1%	7.01	6.85	-2.3%
8	10.72	10.46	-2.4%	7.46	7.29	-2.3%
9	12.86	12.58	-2.1%	8.47	8.22	-2.9%
10	14.53	14.24	-2.0%	9.50	9.28	-2.3%
11	15.92	15.60	-2.1%	10.59	10.34	-2.3%
12	16.90	16.53	-2.1%	11.37	11.10	-2.4%
13	17.33	16.94	-2.2%	11.76	11.48	-2.3%
14	17.94	17.52	-2.3%	12.06	11.74	-2.6%
15	18.13	17.72	-2.2%	12.20	11.87	-2.7%
16	17.73	17.30	-2.4%	12.13	11.86	-2.3%
17	16.80	16.37	-2.6%	12.01	11.77	-2.0%
18	15.07	14.70	-2.5%	11.63	11.43	-1.7%
19	13.46	13.14	-2.3%	11.10	10.89	-1.9%
20	12.39	12.08	-2.5%	10.57	10.32	-2.4%
21	11.64	11.30	-2.9%	10.20	9.91	-2.8%
22	10.27	10.04	-2.2%	9.36	9.14	-2.4%
23	8.91	8.70	-2.3%	8.35	8.14	-2.5%
24	8.02	7.79	-2.8%	7.62	7.42	-2.6%
Averages						
Peak	17.17	16.76	-2.4%			
Part Peak	13.59	13.28	-2.3%			
Off Peak	8.44	8.23	-2.6%	9.38	9.15	-2.4%

Table 5.4: Medium Business Estimated Load Impacts from Hourly Regression – Non-Summer

	Weekday			Weekend		
Hour	Reference kWh	Observed kWh	% Load Impact	Reference kWh	Observed kWh	% Load Impact
1	6.68	6.40	-4.2%	6.71	6.42	-4.3%
2	6.48	6.24	-3.8%	6.46	6.22	-3.6%
3	6.42	6.16	-4.0%	6.15	5.93	-3.6%
4	6.49	6.23	-3.9%	6.30	6.07	-3.6%
5	6.79	6.54	-3.7%	6.42	6.17	-3.9%
6	7.53	7.29	-3.2%	6.63	6.44	-2.9%
7	8.86	8.58	-3.2%	6.96	6.76	-2.9%
8	10.45	10.15	-2.9%	7.23	6.96	-3.8%
9	12.21	11.86	-2.9%	7.78	7.49	-3.8%
10	13.21	12.90	-2.3%	8.49	8.16	-3.9%
11	13.82	13.53	-2.1%	9.03	8.73	-3.3%
12	14.11	13.79	-2.2%	9.27	9.00	-3.0%
13	14.03	13.66	-2.6%	9.29	9.01	-3.1%
14	14.24	13.85	-2.8%	9.29	9.00	-3.2%
15	14.18	13.77	-2.9%	9.28	8.94	-3.7%
16	13.75	13.27	-3.5%	9.18	8.84	-3.7%
17	12.97	12.49	-3.8%	9.13	8.77	-4.0%
18	12.01	11.49	-4.3%	9.20	8.83	-4.1%
19	11.25	10.70	-4.9%	9.19	8.76	-4.6%
20	10.63	10.13	-4.7%	8.96	8.55	-4.5%
21	9.98	9.51	-4.8%	8.66	8.25	-4.7%
22	8.89	8.51	-4.3%	8.02	7.68	-4.3%
23	7.85	7.53	-4.2%	7.29	7.01	-3.8%
24	7.19	6.86	-4.6%	6.78	6.53	-3.7%
Averages						
Peak						
Part Peak	12.54	12.12	-3.5%			
Off Peak	7.91	7.62	-3.7%	7.99	7.69	-3.7%

The average values at the bottom of Tables 5.3 and 5.4 represent average hourly load impacts for the TOU pricing periods. These can be compared to those from the simple difference-in-differences calculations presented in the far right column of Table 4.2. During both the summer and non-summer seasons, average percent load impacts are similar across the two analyses, and the pattern across peak, part-peak, and off-peak periods is the same. That is, all periods experience post-TOU load reductions, and in the summer season, off-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.

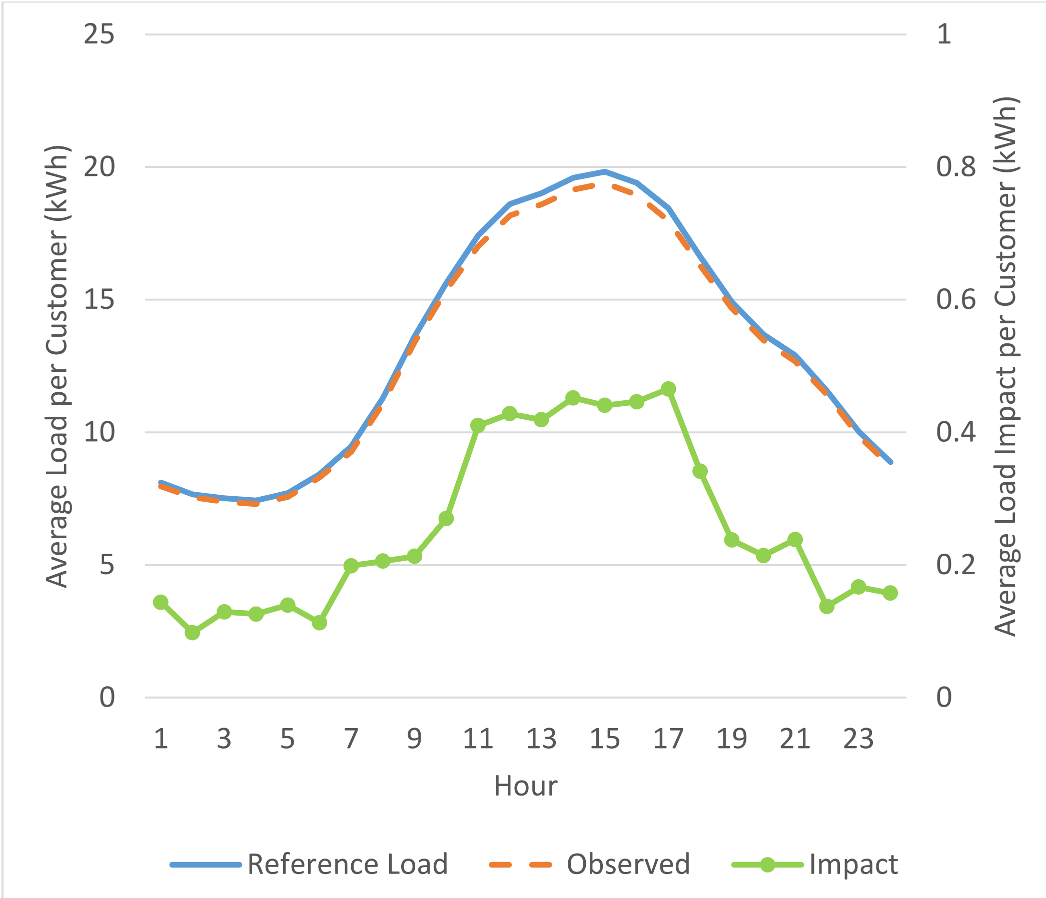
Table 5.5: Medium Business Comparison of Estimated and Calculated Load Impacts, Two Analysis Methods

TOU Pricing Period			% Impact: Simple Difference-in-Differences	% Impact: Fixed-Effects Regression
Summer	Weekdays	Peak	-2.2%	-2.4%
		Part-Peak	-2.0%	-2.3%
		Off-Peak	-2.4%	-2.6%
	Weekends & Holidays	Off-Peak	-2.4%	-2.4%
Non-Summer	Weekdays	Part-Peak	-3.3%	-3.5%
		Off-Peak	-3.5%	-3.7%
	Weekends & Holidays	Off-Peak	-3.8%	-3.7%

Load impact estimates presented thus far are derived from models that include all matched treatment and control small businesses. 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 treatment and control groups. The dependent variable is the difference between the average treatment and control loads 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 also produces difference-in-differences estimates of TOU load impacts, but facilitates the estimation of the effect of weather on TOU load impacts by interacting weather variables with the TOU treatment indicator variable.

Figure 5.4 illustrates average estimated reference loads, actual observed loads, and estimated load impacts on the 2014 August system peak day for all 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 implied average percent load impact during the peak period is -2.3 percent, which is again similar to those found in the previous analyses for peak periods during all summer weekdays. The previously estimated pattern of highest load impacts during off-peak periods does not hold in this analysis. Here, part-peak and off-peak period load impacts average -1.8 and 1.7 percent, respectively, which are lower than the estimates from previous analyses.

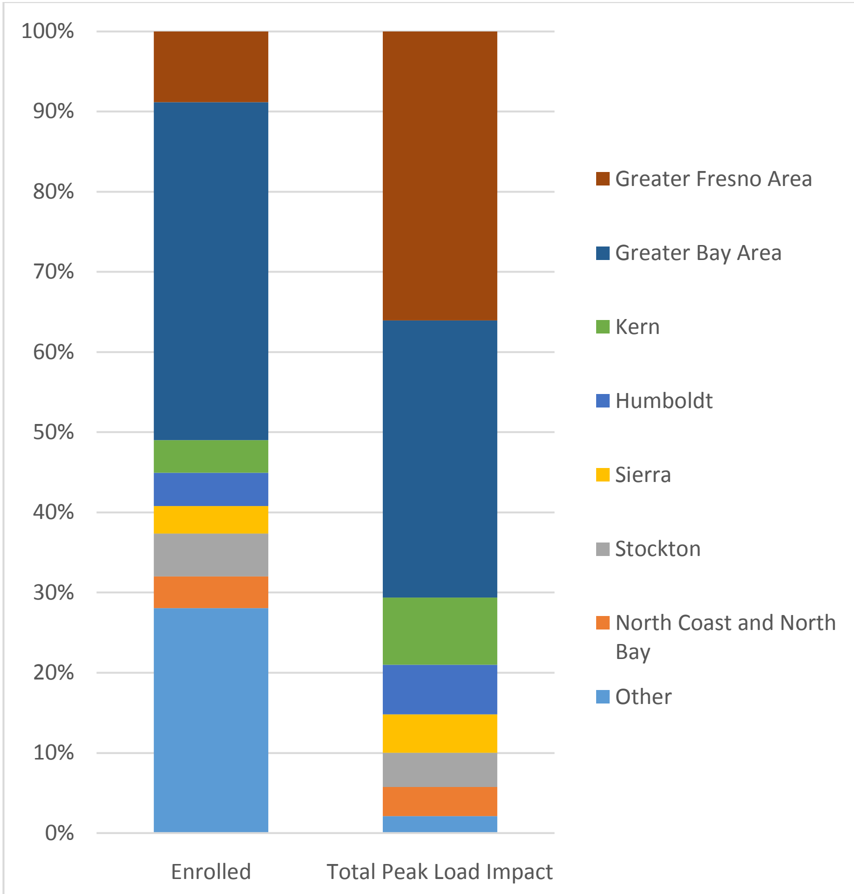
Figure 5.4: August System Peak Reference Loads and Load Impacts for All Medium Businesses (Average Per Customers kWh)



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 2014 system peak day.

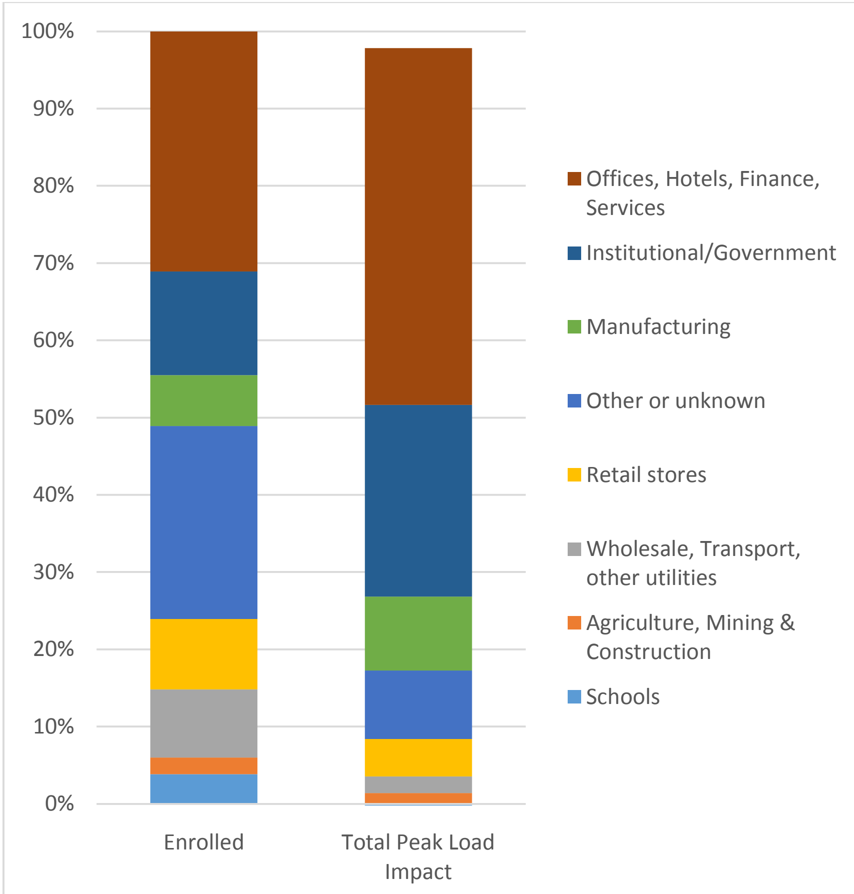
In Figure 5.5, the Greater Fresno Area and Greater Bay Area both contribute large shares to total load reductions, about 35 percent each. For the Greater Bay Area, the load impacts are in proportion to the population, while the Greater Fresno Area only makes up 9 percent of medium business customers. The “Other” LCA group makes up a relatively large percent of the population, 28 percent, but only contributes 2 percent to total load reductions.

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



In Figure 5.6, the "Offices, Hotels, Finance, Services" industry group accounts for nearly half of total load reductions, 48 percent. The next largest contributing sector is "Institutional/Government" with 25 percent. The "Schools" sector experiences estimated load increases of 2.3 percent, which is shown as a negative contribution to load reductions in the graph.

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



6. *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.
- *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.

6.1 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 2014 and November 2015;
- Transitions of agricultural customers in March 2015 and March 2016; 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 2014 *ex-post* load impacts associated with customers transitioned in November 2013. For agricultural customers, we use the 2013 *ex-post* load impacts estimated for customers transitioned in March 2013.

We first developed "observed" loads for each cell (defined as a size group / LCA combination). These models match the *ex-post* models described at the end of Section 3.1 except that the dependent variable is the average treatment customer load in each hour (whereas the *ex-post* model uses the difference between average treatment and control customer loads as the dependent variable). The models use 2014 data, thus producing simulations of customer loads while on the TOU rate for each required day type and weather scenario.

We develop four sets of results associated with 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. CAISO-coincident scenarios were added to the various load impacts studies this program year based on stakeholder interest. The studies conducted in prior years included only utility-specific weather scenarios. Note that those scenarios were updated for this program year as well.

The load impacts for each cell and scenario are simulated from the *ex-post* models described at the end of Section 3.1. Specifically, these models estimate a stand-alone TOU load impact as well as the effect of weather on load impacts (via interactions between the TOU and weather variables). We simulate the scenario-specific load impacts using the weather conditions corresponding to the scenario in question.

$$Load\ impact_{c,s} = b_c^{TOU} + b_c^{TOU,CDD} \times CDD_{c,s} + b_c^{TOU,HDD} \times HDD_{c,s}$$

This equation shows that the load impact for customer cell *c* in scenario *s* is equal to the estimated non-weather TOU load impact (b_c^{TOU}) for cell *c* plus the scenario-specific weather conditions ($CDD_{c,s}$ and $HDD_{c,s}$) multiplied by the corresponding estimated effects of weather on TOU load impacts for cell *c* ($b_c^{TOU,CDD}$ and $b_c^{TOU,HDD}$).

These load impacts are then matched to the TOU loads for the corresponding customer cell and scenario. 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 TOU loads.

Weather Sensitivity of Load Impacts

The methodology described above produces estimated TOU load impacts that are sensitive to weather conditions. That is, the regression models produce estimates of the effects of CDDs and HDDs for each customer cell (*c*) during each season, which are then combined with cell- and weather scenario-specific levels of CDDs and HDDs to produce estimates of TOU load impacts.

The estimated weather effects vary across seasons, customer sizes, and customer cells. For example, small business customers in the Greater Bay Area LCA experience larger load reductions on hot summer days than small businesses in the Greater Fresno Area LCA. Medium business customers in both LCAs experience larger load reductions on hotter summer days.

Table 6.1 shows estimated average hourly per-customer load impacts (kWh) during the peak period for all small and medium businesses on summer and non-summer days with several possible average temperatures.[19] For small businesses, load reductions in the non-summer season get smaller as temperatures increase while the opposite is true in the summer season. For medium businesses, load reductions are larger on warmer days in both seasons.

[19] Peak periods are defined as 1:00 to 6:00 p.m. during summer months and 4:00 to 9:00 p.m. during non-summer months in accordance with *ex-ante* resource adequacy requirements.

Table 6.1: Estimated Load Reductions under Various Weather Conditions

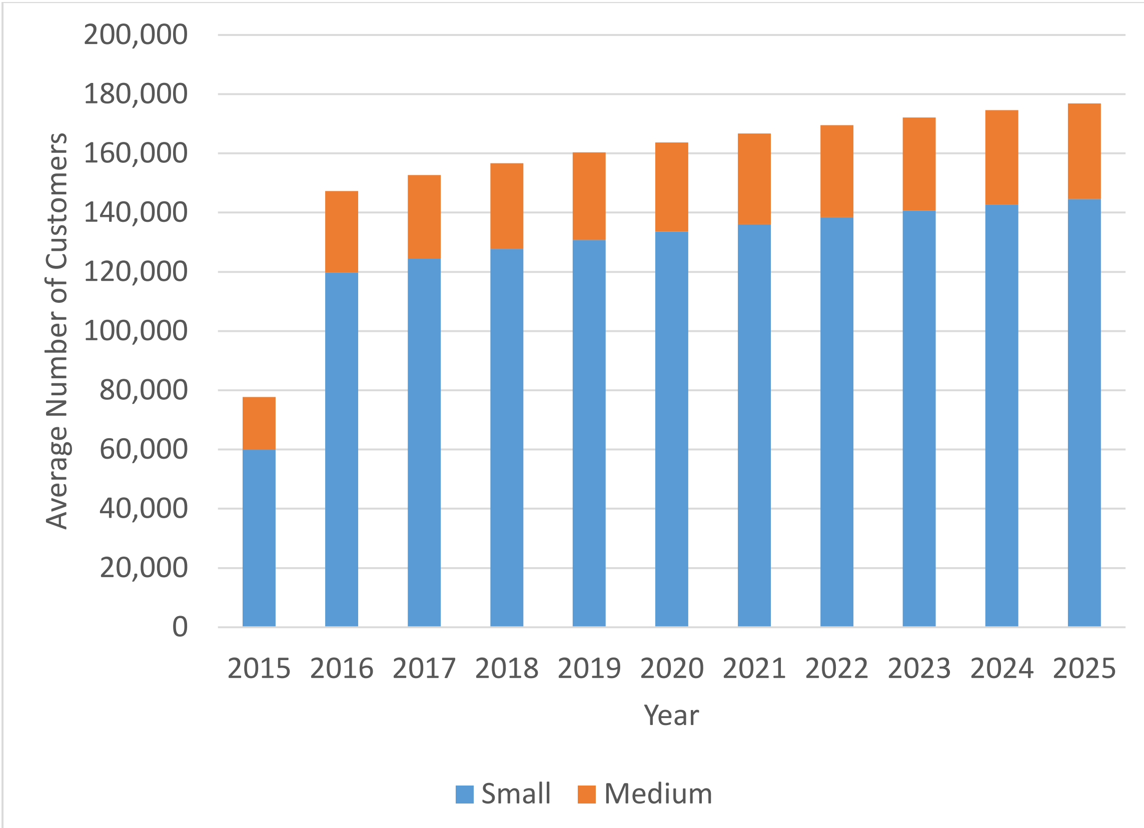
		Average Hourly Load Impact (kWh)	
Season	**Avg. Daily Temperature**	**Small Business**	**Medium Business**
Non-Summer	40	0.04	0.33
Non-Summer	50	0.04	0.45
Non-Summer	60	0.03	0.57
Summer	70	0.06	0.33
Summer	80	0.07	0.44
Summer	90	0.08	0.56

Results

Figure 6.1 shows the incremental customer TOU enrollments by year for SMB customers, where each year shows an average across months. The large increase between 2015 and 2016 is due to the transition of approximately 79,000 customers to TOU rates in November 2015. The remaining growth over time represents new customers that are placed on TOU rates by default.

In addition to the enrollments shown in Figure 6.1, approximately 6,000 agricultural customers will be transitioned to a TOU rate in March 2015 and 7,500 in March 2016. We hold the total agricultural enrollment value of 13,615 constant for the remainder of the forecast period.

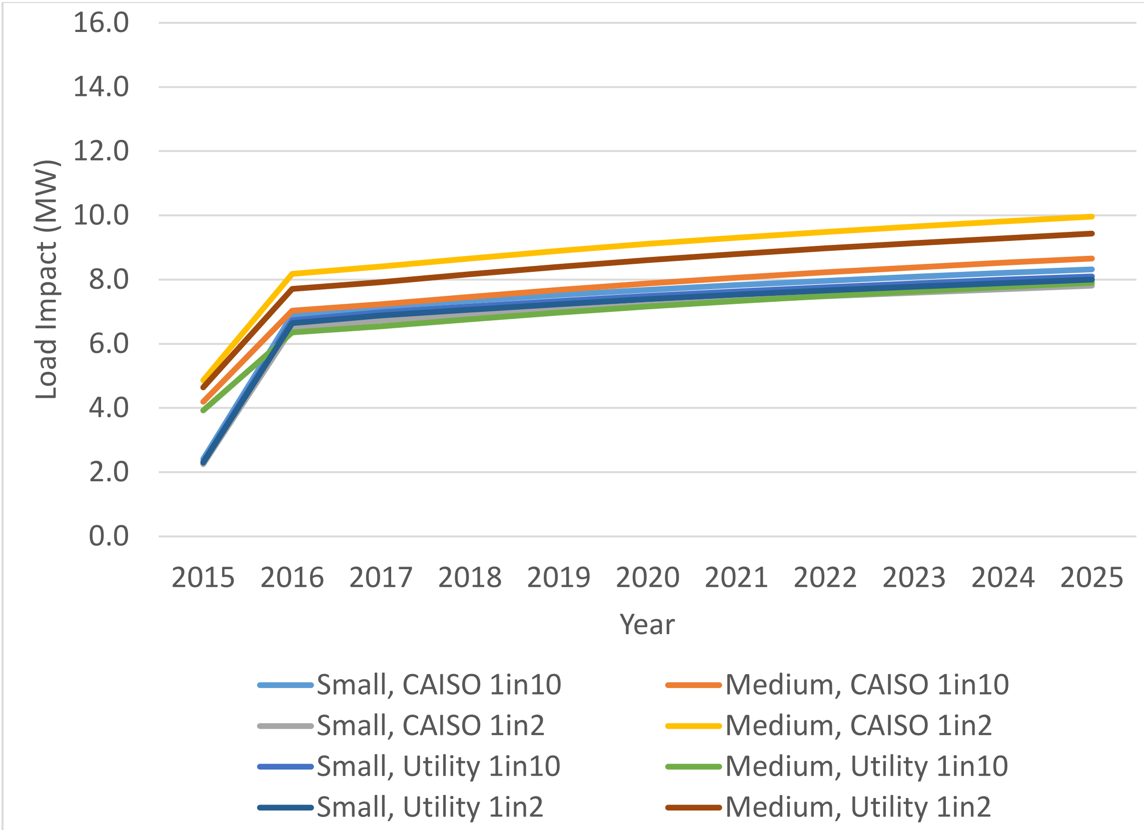
Figure 6.1: Non-Residential TOU Enrollments, Incremental SMB Customers



Figures 6.2 and 6.3 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. [20]

[20] In Figure 6.2, estimated load impacts for medium businesses are larger during 1-in-2 weather scenarios than they are for 1-in-10 (yellow and dark red lines lie above the orange and green lines). It is often the case during non-summer months that 1-in-2 weather scenarios are warmer than 1-in-10 conditions. Combined with the weather sensitivity illustrated in Table 6.1, medium businesses are therefore expected to have higher non-summer load reductions during 1-in-2 conditions.

Figure 6.2: January Peak Day *Ex-Ante* Load Impacts by Group and Weather Scenario



A comparison of Figures 6.2 and 6.3 indicates that load impacts tend to be higher in August than January. For example, in the 2016 utility-specific 1-in-2 peak forecast, load impacts are 4.2 MW higher in August than in January (combining across the small and medium customer groups).

Figure 6.3: August Peak Day *Ex-Ante* Load Impacts by Group and Weather Scenario

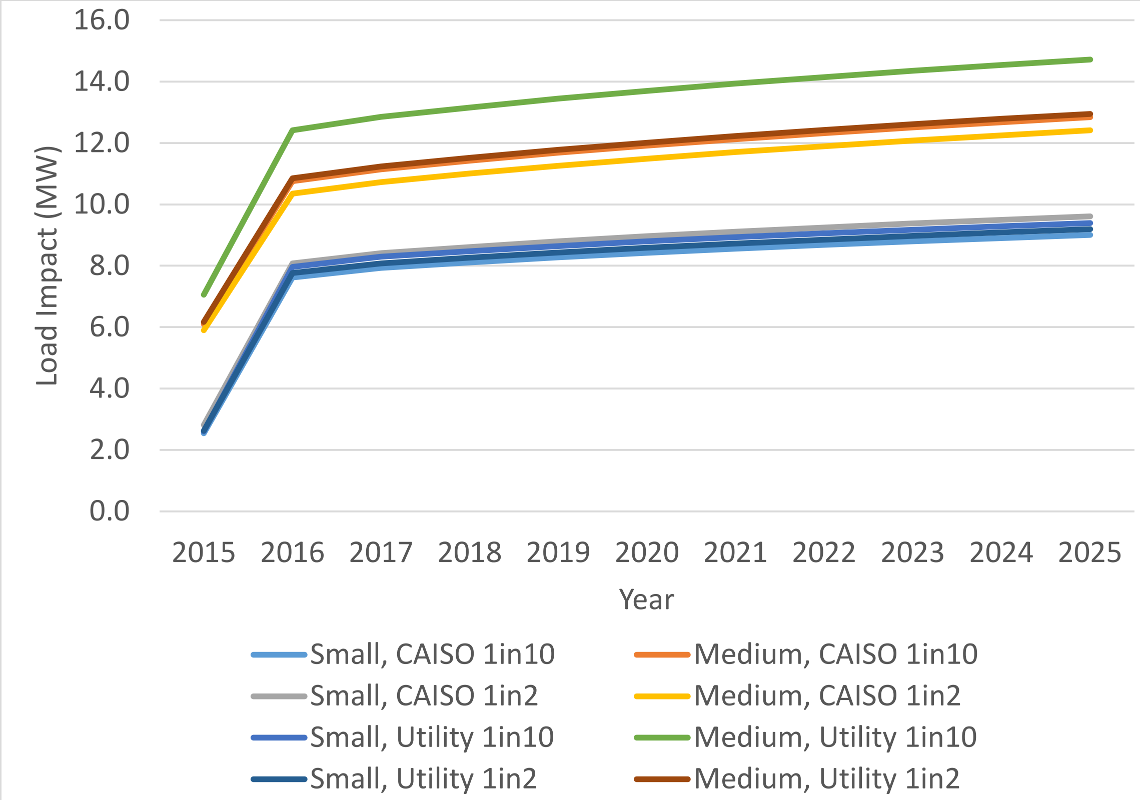


Figure 6.4 provides an illustration of the hourly reference loads, observed loads, and load impacts for the August 2016 utility-specific 1-in-2 peak day. Load reductions are forecast for each hour of the day, with the percentage reduction ranging from 1.7 to 3.1 percent.

Figure 6.4: Hourly *Ex-Ante* Load Impacts, All Incremental Customers, August 2016 Utility 1-in-2 Peak Day

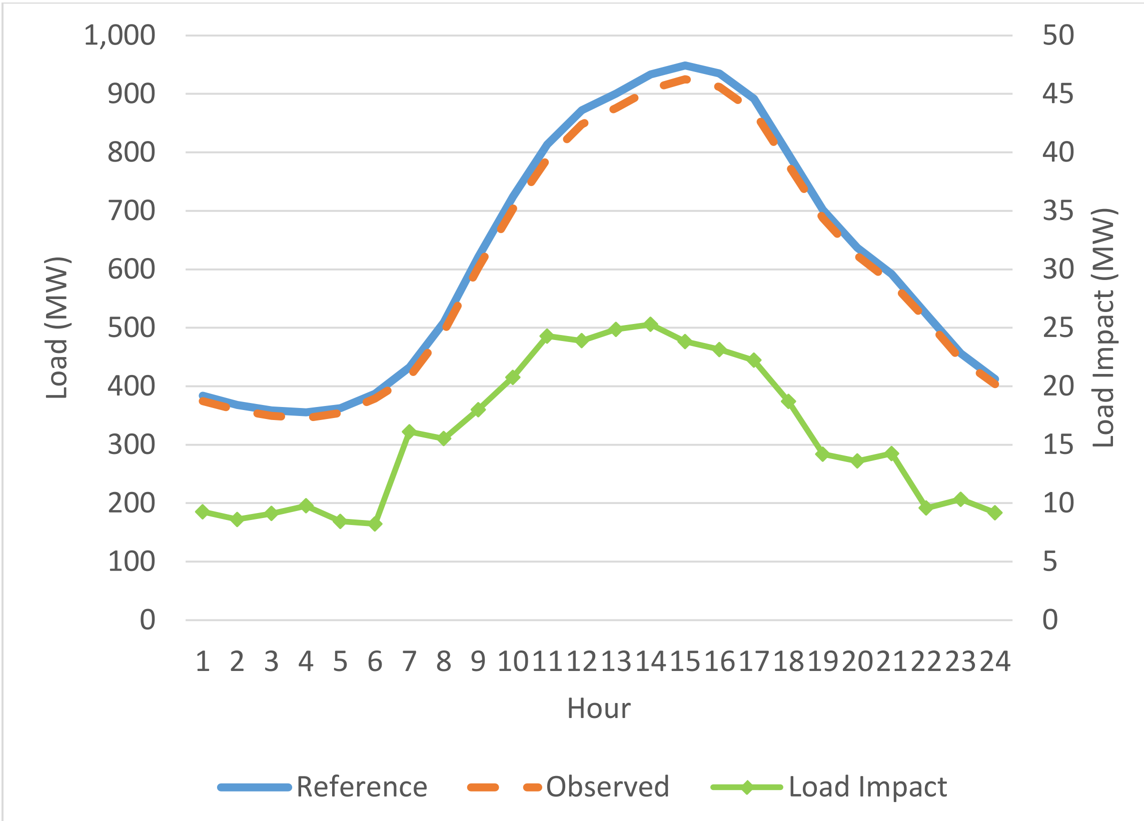
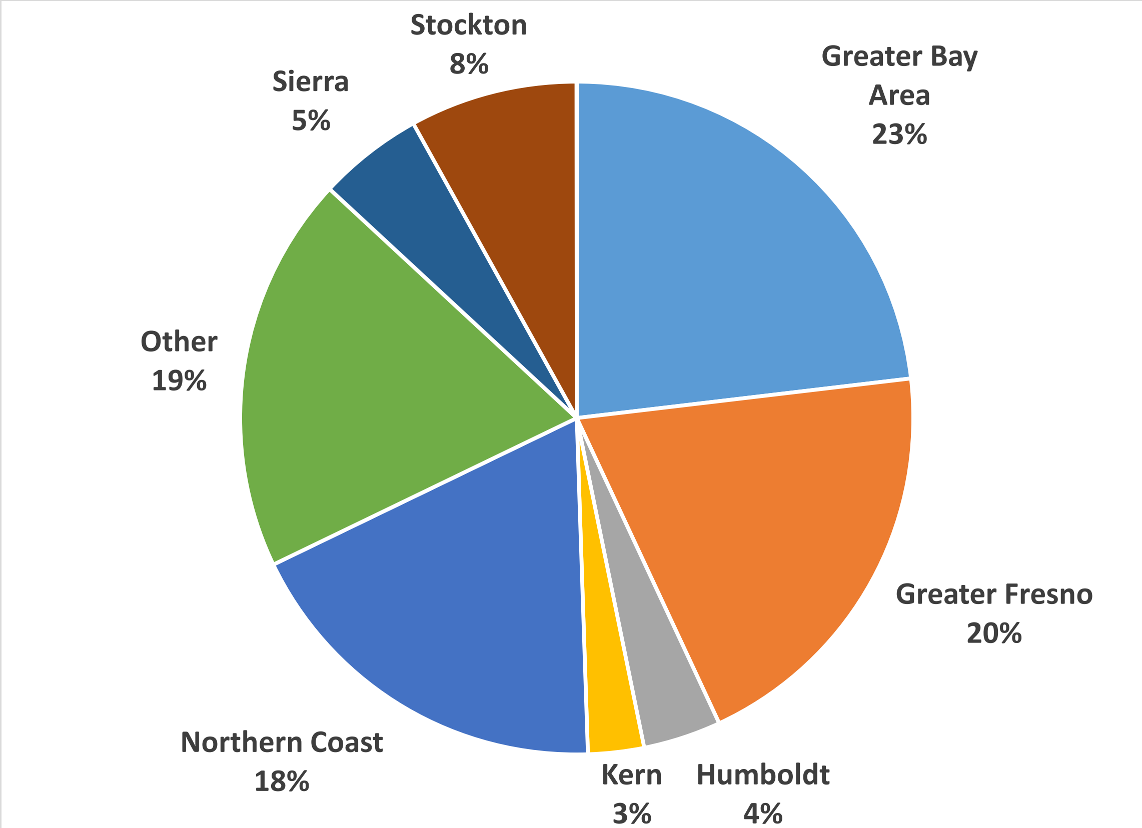


Figure 6.5 shows the distribution of August 2016 load impacts by LCA. The Greater Bay Area LCA accounts for the largest share.

Figure 6.5: August 2016 Peak Day Load Impacts by LCA, Utility-Specific 1-in-2 Weather



6.2 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 2013 program year). However, 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 this analysis and also added scenarios that correspond to CAISO-coincident conditions. (The updated weather scenarios correspond to utility-specific 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.[21]

For the recently transitioned customers, the *ex-ante* load impacts are based on our SMB *ex-post* forecast for customers transitioned in November 2013. The methods follow those used to develop the incremental TOU load impact forecast described in Section 6.1, but applying a different set of enrollments.

Results

The enrollment forecast contains 400,797 embedded TOU customers. Of these, 82,871 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 317,926) 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 82,871) 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 6.6 illustrates the enrollments by group.

[21] 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.

Figure 6.6: Embedded TOU Customer Enrollments by Group

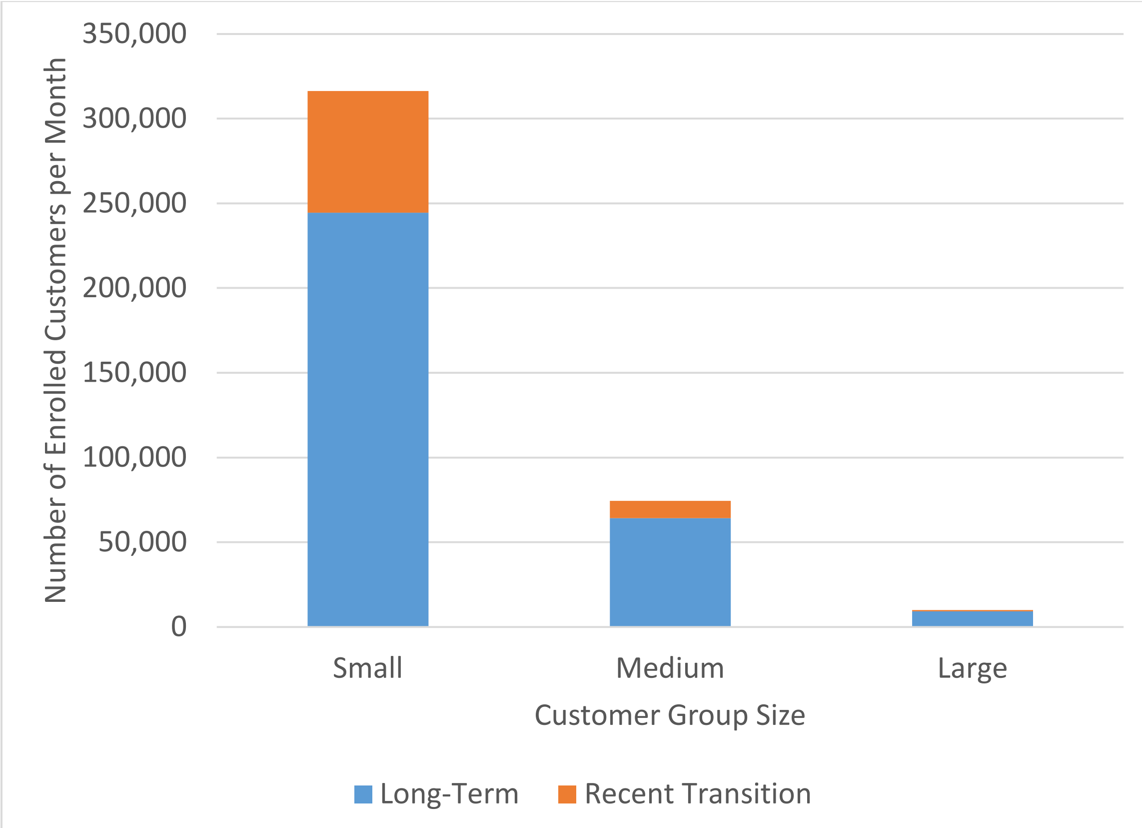


Figure 6.7 shows the embedded TOU load impacts by month and weather scenario. The load impacts are averaged across 1:00 to 6:00 p.m. for April through October and 4:00 to 9:00 p.m. for November through March. Summer load impacts range from 250 to 300 MW and non-summer load impacts are approximately 50 MW. As expected, the utility-specific 1-in-10 peak day load impacts are the highest in the summer.

Figure 6.7: Embedded TOU Load Impacts by Month and Weather Scenario

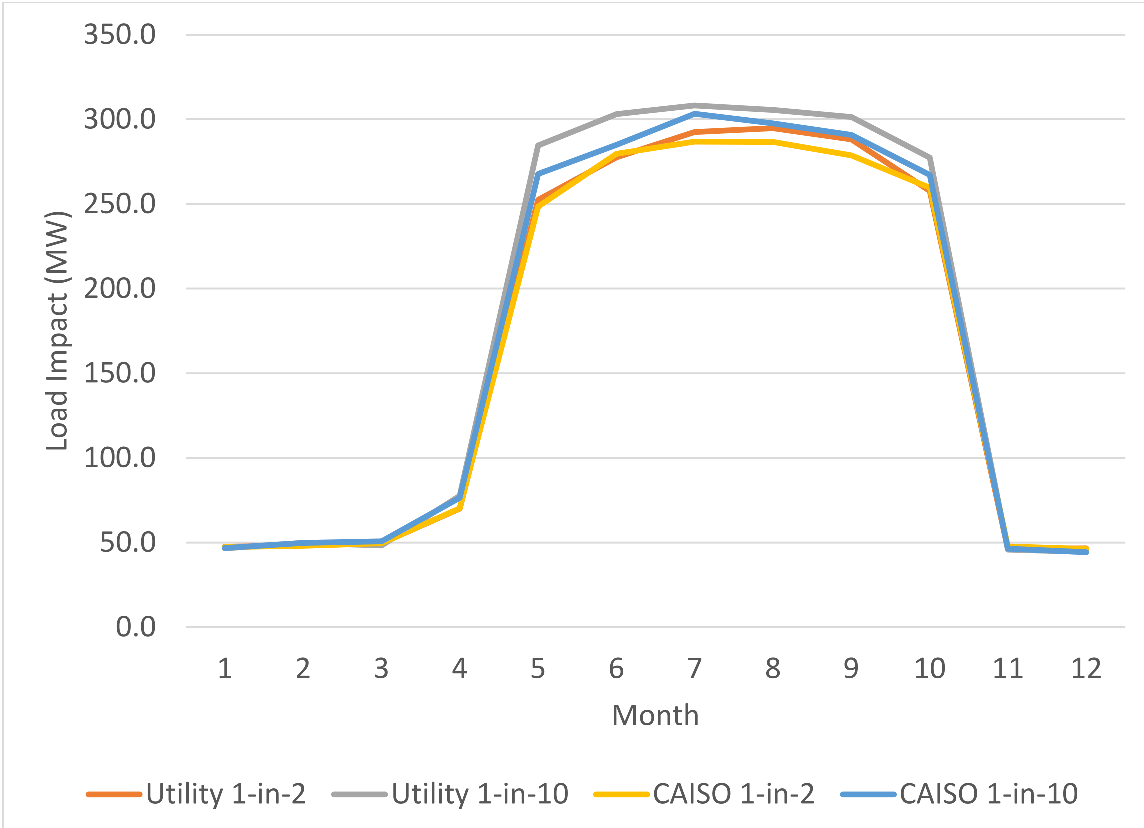


Figure 6.8 shows the distribution of embedded TOU load impacts by LCA, using the August utility-specific 1-in-2 peak day scenario. The Greater Bay Area has the largest share of load impacts.

Figure 6.8: Embedded TOU Load Impacts by LCA, August 2016 Utility 1-in-2 Peak Day

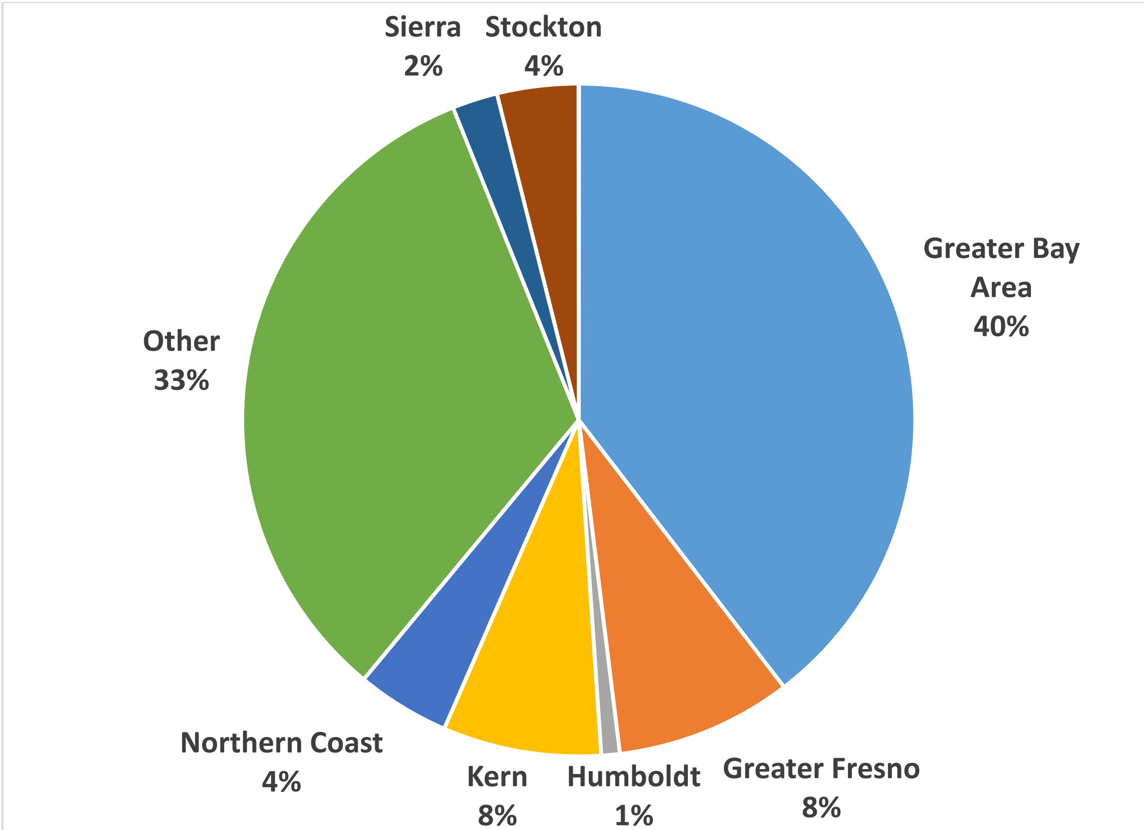
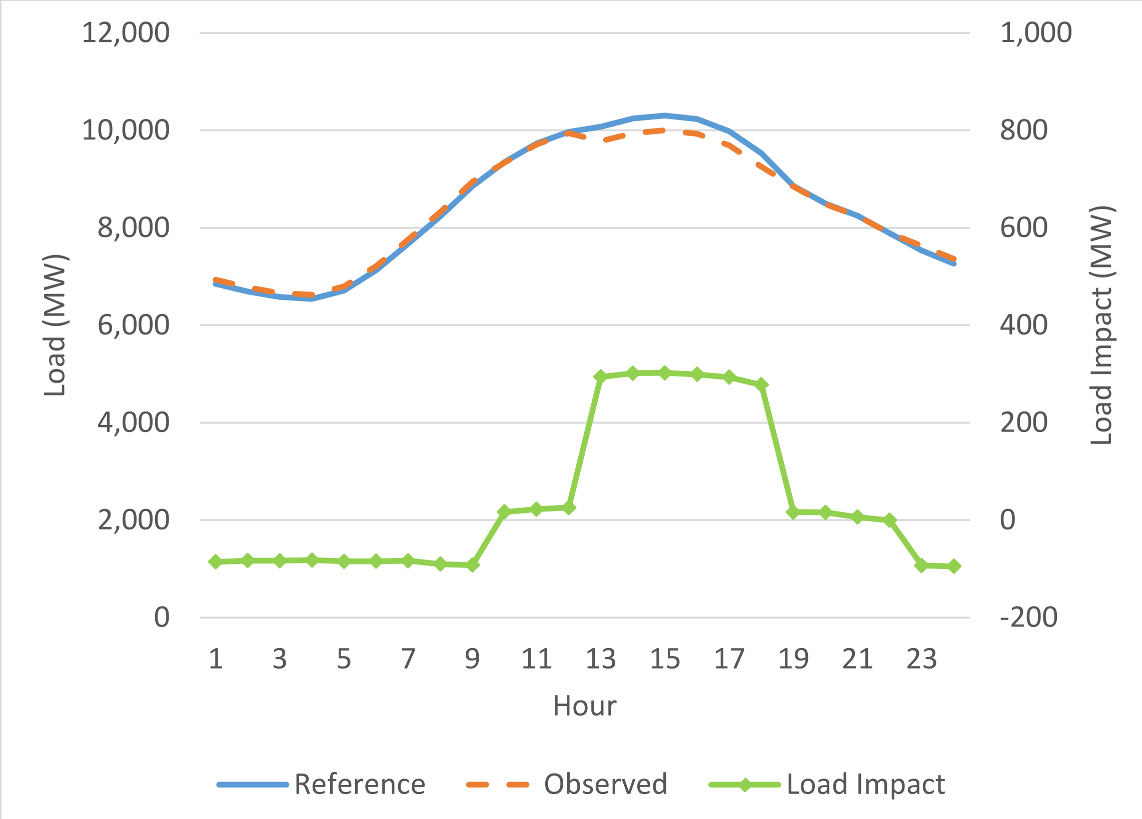


Figure 6.9 shows the hourly reference loads, observed loads, and load impacts for the August utility-specific 1-in-2 peak day. You can see the effect of the simulated embedded load impacts, which contain load reductions during peak hours and load increases in off-peak hours. This pattern of TOU demand 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 customers have tended to differ from this pattern, often displaying load reductions across all pricing periods.

Figure 6.9: Hourly Embedded TOU Load Impacts, August 2016 Utility 1-in-2 Peak Day



7. 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 comparisons to the prior study are hampered by the fact that the analysis was conducted by rate group (*e.g.*, A1 and A10) whereas this study was conducted by customer size group (*e.g.*, under 20 kW and 20 to 200 kW).

7.1 Previous versus current ex-post

Table 7.1 compares the *ex-post* load impacts from the previous and current studies. The summer values represent the August peak day 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. The previous study was conducted for A1 customers while the current study was conducted for all small (under 20 kW) SMB customers. As a result, the average customer size is somewhat lower in the current study. In addition, the percentage load impacts are lower in the current study during summer and non-summer months.

Table 7.1 Current vs. Previous *Ex-Post* Load Impacts, *A1 / Under 20kW*

Season	Result	Previous Study (A1)	Current Study (Under 20kW)
Both	# SAIDs	220,000	80,019
Summer	Reference (MW)	805	206
	Load Impact (MW)	30	5
	Per-SAID reference (kW)	3.66	2.58
	Per-SAID load impact (kW)	0.14	0.06
	% Load Impact	3.7%	2.4%
Non-summer	Reference (MW)	441	126
	Load Impact (MW)	15	3
	Per-SAID reference (kW)	2.01	1.58
	Per-SAID load impact (kW)	0.07	0.04
	% Load Impact	3.3%	2.2%

Table 7.2 provides the same comparisons for the A10 and medium-sized customers. Once again, the difference in classifications (by rate versus by size) produces lower per-customer reference loads and load impacts in the current study. The percentage load impacts were lower in the current study.

Table 7.2 Current vs. Previous *Ex-Post* Load Impacts, *A10 / 20 to 200kW*

Season	Result	Previous Study (A10)	Current Study (20 to 200kW)
Both	# SAIDs	5,211	7,442
Summer	Reference (MW)	190	140
	Load Impact (MW)	7	3
	Per-SAID reference (kW)	36.4	18.8
	Per-SAID load impact (kW)	1.4	0.4
	% Load Impact	3.8%	2.3%
Non-summer	Reference (MW)	104	78
	Load Impact (MW)	6	4
	Per-SAID reference (kW)	20	10.5
	Per-SAID load impact (kW)	1.2	0.5
	% Load Impact	5.9%	4.8%

7.2 Previous versus current ex-ante

Table 7.3 compares the incremental *ex-ante* load impact forecasts from the previous and current studies. In each case, the information represents August 2015 peak day load impacts with utility-specific 1-in-2 weather conditions. The current study includes many fewer customers (71,380 versus 213,940), along with lower per-customer reference loads, load impacts, and percentage load impacts.

Table 7.3 Previous vs. Current *Ex-Ante* Incremental Load Impacts

Result	Previous *Ex-Ante*, Incremental	Current *Ex-Ante*, Incremental
# SAIDs	213,940	71,380
Reference (MW)	1,883	464
Load Impact (MW)	77.9	10.6
Per-SAID reference (kW)	8.80	6.50
Per-SAID load impact (kW)	0.36	0.15
% Load Impact	4.1%	2.3%

In each study, the incremental *ex-ante* load impacts are based on the *ex-post* load impacts. Table 7.4 shows the *ex-post* percentage load impacts for the summer peak period by rate group from each study. Recall that the current *ex-post* study did not include agricultural customers. For these customers, we applied the *ex-post* load impacts from the previous study.

Notice that the SMB customer load impacts were uniformly lower in the current study than in the previous study. While there is some mismatch between the groups (*i.e.*, the "medium" customer group in the current study includes both A1 and A10 customers), this doesn't explain why load impacts are lower for both SMB sub-groups in the current study.

Table 7.4: Comparison of Summer Peak Percentage Load Changes

Customer Group	Previous *Ex-Post*	Current *Ex-Post*
A1 / Small (Under 20kW)	3.7%	2.1%
A10 / Medium (20 to 200kW)	4.2%	2.4%
Agricultural	19.1%	N/A

7.3 Previous ex-ante versus current ex-post

Table 7.5 compares the previous study's August peak day 2014 *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 somewhat higher (99,945 versus 87,461), which may be due to the failure to transition agricultural customers in early 2014 as had been planned. In addition, the per-customer reference load, load impact, and percentage load impact were substantially higher in last year's *ex-ante* forecast. It is not entirely clear why the average size differs as much as it does, given that the analyses have roughly equal shares of usage by LCA and size category. It appears that the previous study may have overstated average customer size because it was based on rate groups rather than size groups, whereas the enrollment forecasts were developed for size groups. For example, the medium-sized customers we analyze contain both A1 and A10 customers, and we found the average size of the medium-sized customers to be considerably lower than the A10 customers analyzed in previous study. Scaling up per-customer results for A10 customers using medium-sized customer enrollments would result in per-customer reference loads that are larger than we would expect.

Table 7.5 Previous *Ex-Ante* vs. Current *Ex-Post* Incremental Load Impacts

Result	Previous *Ex-Ante*, Incremental	Current *Ex-Post*
# SAIDs	99,945	87,461
Reference (MW)	907	346
Load Impact (MW)	35.9	8.1
Per-SAID reference (kW)	9.07	3.96
Per-SAID load impact (kW)	0.36	0.09
% Load Impact	4.0%	2.3%

7.4 Current ex-post versus current ex-ante

Table 7.6 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 2015 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). 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.

Table 7.6 *Ex-Post* vs. Incremental *Ex-Ante* Load Impacts

Result	Current *Ex-Post*	Current *Ex-Ante*, Incremental
# SAIDs	87,461	71,380
Reference (MW)	346	464
Load Impact (MW)	8.1	10.6
Per-SAID reference (kW)	3.96	6.50
Per-SAID load impact (kW)	0.09	0.15
% Load Impact	2.3%	2.3%

Table 7.7 compares the *ex-post* and *ex-ante* enrollments by customer group. There are three notable differences between them: *ex-ante* enrollments are lower than *ex-post* enrollments by 16,081 service accounts (or 18.4 percent); the *ex-post* forecast includes a much larger share of under 20kW customers (91.5 percent versus 68.8 percent); and the *ex-ante* study includes agricultural customers, which were not included in the *ex-post* study because none of them were transitioned in early 2014.

The effect of the change in the distribution of customers by group is to increase the average customer size and load impact. The percentage load impact is the same for the two studies, at 2.3 percent.

Table 7.7 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)	80,019	49,078
	Medium (20 to 200 kW)	7,442	16,182
	Agricultural	0	6,120
	Total	87,461	71,380
Share of SAIDs	Small (under 20kW)	91.5%	68.8%
	Medium (20 to 200 kW)	8.5%	22.7%
	Agricultural	0.0%	8.6%

Table 7.8 compares the key components of the two analyses. In addition to the enrollment differences described above, the difference in weather conditions contributes to higher *ex-ante* load impacts. The higher *ex-ante* temperatures increase the total load impact by approximately 1.2 MW.

Table 7.8: *Ex-Post* versus *Ex-Ante* Factors

Factor	*Ex-Post*	*Ex-Ante*	Expected Impact
Weather	84.8 degrees Fahrenheit during HE 14 to 18.	89.0 degrees Fahrenheit during HE 14 to 18 of a utility-specific 1-in-2 August peak day.	Hotter *ex-ante* weather increases the reference load and load impact. The difference in temperatures increases the load impact by approximately 1.2 MW during HE 14 to 18.
Enrollment	87,461 SAIDs.	71,380 SAIDs.	There are both fewer service accounts in the *ex-ante* load impacts (representing fewer customer transitions relative to the *ex-post* analysis), but the customers are much less likely to be in the under 20kW group (91.5% in the *ex-post* vs. 68.8% in *ex-ante*). Also, the *ex-ante* includes 6,120 Ag accounts, whereas none were in the *ex-post* study.
Methodology	Group-level aggregated regressions to explain differences between average treatment and control group loads.	Group-level aggregated regressions to explain differences between average treatment and control group loads.	No effect. The *ex-post* models required to develop the various scenarios are also applied to the *ex-ante* study.

8. Recommendations

As more SMB and agricultural customers are transitioned to TOU rates, it will become increasingly difficult to estimate TOU load impacts due to the paucity of eligible control-group customers. Load impact analyses would be improved if PG&E could withhold a set of customers from the transition process that could serve as a control group. Our assumption that this is impractical for a number of reasons (*e.g.*, ensuring that control-group customers do not receive TOU messaging; or the potential for confusion and complaints that may arise when some customers are transitioned while other similarly situated customers are not).

In the absence of a viable control group, the alternative methods for estimating TOU load impacts for newly transitioned customers include within-treatment comparisons of loads before and after TOU migration; or estimating how customers change their usage profile following the changes in TOU pricing seasons (*e.g.*, by comparing April and May load profiles, which are exposed to different TOU prices). While we do not expect these methods to be as effective as a control-group-based methodology, they provide some means of estimating TOU load impacts.

Appendices

The following Appendices accompany this report. Appendix A is a detailed comparison and tests for significant differences between matched SMB treatment and control customers on the bases of usage levels, usage patterns, geography, and industry. Appendix B contains a description of an alternative medium business matching method and implied TOU impacts. The additional appendices are Excel files that can produce the tables required by the Protocols.

Appendix C PG&E Ex-Post Load Impact Tables
Appendix D PG&E Incremental Ex-Ante Load Impact Tables
Appendix E PG&E Embedded Ex-Ante Load Impact Tables

Appendix A

Table A.1: Small Business (Below 20 kW) Treatment vs. Control Group Comparison

Category	Variable	Treated	Control	t	p>t
Pre-TOU Monthly Consumption (kWh)	January 2013	1102	1111	-0.5	0.6
	February 2013	968	975	-0.4	0.7
	March 2013	1030	1033	-0.1	0.9
	April 2013	1014	1017	-0.2	0.9
	May 2013	1073	1078	-0.3	0.8
	June 2013	1096	1097	0.0	1.0
	July 2013	1182	1175	0.3	0.8
	August 2013	1159	1150	0.5	0.7
Summer Weekday Consumption (kWh) by Time Period	12 to 3 AM	3.2	3.2	-1.0	0.3
	3 to 6 AM	3.1	3.2	-0.9	0.4
	6 to 9 AM	3.8	3.8	0.5	0.6
	9 AM to 12 PM	6.1	6.0	0.9	0.4
	12 to 3 PM	6.9	6.8	0.9	0.4
	3 to 6 PM	6.6	6.5	0.9	0.4
	6 to 9 PM	4.9	4.9	-0.1	0.9
	9 PM to 12 AM	3.8	3.9	-0.7	0.5
Winter Weekday Consumption (kWh) by Time Period	12 to 3 AM	3.1	3.2	-1.2	0.2
	3 to 6 AM	3.1	3.2	-1.0	0.3
	6 to 9 AM	4.1	4.1	0.1	0.9
	9 AM to 12 PM	5.9	5.9	0.5	0.6
	12 to 3 PM	6.1	6.0	0.5	0.6
	3 to 6 PM	5.7	5.6	0.4	0.7
	6 to 9 PM	4.6	4.7	-0.6	0.6
	9 PM to 12 AM	3.6	3.7	-1.1	0.3
Summer Weekday Share of	12 to 3 AM	9.3%	9.4%	-0.5	0.6
	3 to 6 AM	8.9%	9.1%	-1.8	0.1
	6 to 9 AM	9.9%	9.9%	0.0	1.0

Category	Variable	Treated	Control	t	p>t
Consumption (kWh) by Time Period	9 AM to 12 PM	15.5%	15.4%	0.8	0.4
	12 to 3 PM	17.2%	17.2%	0.3	0.8
	3 to 6 PM	16.2%	16.1%	0.8	0.4
	6 to 9 PM	12.2%	12.2%	-0.1	0.9
	9 PM to 12 AM	10.8%	10.7%	0.3	0.8
Winter Weekday Share of Consumption (kWh) by Time Period	12 to 3 AM	9.1%	9.2%	-0.2	0.8
	3 to 6 AM	8.9%	9.1%	-2.1	0.0
	6 to 9 AM	11.0%	10.9%	1.2	0.2
	9 AM to 12 PM	16.1%	16.3%	-1.5	0.1
	12 to 3 PM	16.5%	16.6%	-0.6	0.6
	3 to 6 PM	15.4%	15.2%	2.0	0.0
	6 to 9 PM	12.7%	12.6%	0.7	0.5
	9 PM to 12 AM	10.3%	10.2%	1.0	0.3
Climate Zone	P - Clear Lake	--	--	--	--
	Q - Santa Cruz	0.0	0.0	-3.7	0.0
	R - Fresno	0.1	0.1	5.4	0.0
	S - Stockton/Sacramento	0.1	0.1	0.0	1.0
	T - Coastal Bay Area	0.4	0.4	-0.2	0.9
	V - Humboldt	0.0	0.0	-0.1	0.9
	W - Kern	0.0	0.0	-0.9	0.4
	X - San Jose/Concord	0.3	0.3	0.4	0.7
	Y - Sierras	0.0	0.0	-9.7	0.0
	Z - Sierras	0.0	0.0	-3.0	0.0
Industry Type	11 - Agriculture, Forestry, Fishing and Hunting	0.0	0.0	0.9	0.4
	22 - Utilities	0.0	0.0	-1.0	0.3
	23 - Construction	0.0	0.0	1.0	0.3
	31 - Manufacturing - Food and finished products	0.0	0.0	-0.1	0.9
	32 - Manufacturing - Primary materials	0.0	0.0	-1.5	0.1
	33 - Manufacturing - Metals and machinery	0.0	0.0	0.8	0.4
	42 - Wholesale Trade	0.0	0.0	-0.3	0.7
	44 - Retail Trade	0.1	0.1	1.0	0.3
	45 - Retail Trade	0.0	0.0	0.5	0.6
	48 - Transportation	0.0	0.0	-1.1	0.3
	49 - Warehousing, Storage and Couriers	0.0	0.0	0.0	1.0
	51 - Information	0.0	0.0	-1.6	0.1
	52 - Finance and Insurance	0.0	0.0	1.6	0.1
	53 - Real Estate and Rental and Leasing	0.1	0.1	-0.7	0.5
	54 - Professional, Scientific, and Technical Services	0.0	0.0	1.4	0.2

Category	Variable	Treated	Control	t	p>t
	55 - Management of Companies and Enterprises	0.0	0.0	-0.3	0.8
	56 - Waste Management and Remediation Services	0.0	0.0	0.2	0.8
	61 - Educational Services	0.0	0.0	1.6	0.1
	62 - Health Care and Social Assistance	0.0	0.0	-0.3	0.8
	71 - Arts, Entertainment, and Recreation	0.0	0.0	0.2	0.9
	72 - Accommodation and Food Services	0.1	0.1	-0.1	1.0
	81 - Other Services (except Public Administration)	0.1	0.1	-0.6	0.6
	92 - Public Administration	0.0	0.0	0.3	0.8
	0 - Unclassified or other	0.0	0.0	0.6	0.6

Table A.2: Medium Business (20 to 199.99 kW) Treatment vs. Control Group Comparison

Category	Variable	Treated	Control	t	p>t
Pre-TOU Monthly Consumption (kWh)	January 2013	6875	6944	-0.6	0.5
	February 2013	6124	6154	-0.3	0.8
	March 2013	6722	6722	0.0	1.0
	April 2013	6894	6874	0.2	0.9
	May 2013	7469	7470	0.0	1.0
	June 2013	7679	7735	-0.5	0.6
	July 2013	8320	8362	-0.3	0.8
	August 2013	8225	8275	-0.4	0.7
Summer Weekday Consumption (kWh) by Time Period	12 to 3 AM	20.3	20.8	-1.2	0.2
	3 to 6 AM	20.7	21.2	-1.0	0.3
	6 to 9 AM	30.5	30.6	-0.2	0.9
	9 AM to 12 PM	44.5	44.2	0.4	0.7
	12 to 3 PM	49.8	49.5	0.4	0.7
	3 to 6 PM	46.5	46.7	-0.3	0.7
	6 to 9 PM	35.3	35.5	-0.4	0.7
	9 PM to 12 AM	25.9	26.5	-1.2	0.2
Winter Weekday Consumption (kWh) by Time Period	12 to 3 AM	18.6	19.0	-1.1	0.3
	3 to 6 AM	19.8	20.3	-1.2	0.2
	6 to 9 AM	30.4	30.6	-0.4	0.7
	9 AM to 12 PM	39.8	39.5	0.5	0.6
	12 to 3 PM	40.3	39.8	0.7	0.5
	3 to 6 PM	36.4	36.3	0.2	0.9
	6 to 9 PM	29.7	29.9	-0.3	0.8
	9 PM to 12 AM	22.5	22.9	-0.9	0.4
Summer Weekday Share of Consumption (kWh) by Time Period	12 to 3 AM	7.0%	7.2%	-2.5	0.0
	3 to 6 AM	7.1%	7.2%	-1.6	0.1
	6 to 9 AM	11.1%	10.8%	2.3	0.0
	9 AM to 12 PM	17.0%	16.8%	1.9	0.1
	12 to 3 PM	18.9%	18.6%	2.8	0.0
	3 to 6 PM	17.1%	17.1%	0.2	0.9
	6 to 9 PM	12.8%	13.0%	-1.4	0.2
	9 PM to 12 AM	9.1%	9.4%	-2.7	0.0
Winter Weekday Share of Consumption (kWh) by Time Period	12 to 3 AM	7.4%	7.5%	-2.3	0.0
	3 to 6 AM	7.8%	7.9%	-2.6	0.0
	6 to 9 AM	12.6%	12.5%	1.1	0.3
	9 AM to 12 PM	17.6%	17.2%	3.1	0.0
	12 to 3 PM	17.5%	17.2%	2.8	0.0
	3 to 6 PM	15.5%	15.5%	-0.1	0.9
	6 to 9 PM	12.7%	12.8%	-1.1	0.3
	9 PM to 12 AM	9.0%	9.3%	-3.1	0.0

Category	Variable	Treated	Control	t	p>t
Climate Zone	P - Clear Lake	--	--	--	--
	Q - Santa Cruz	0.0	0.0	-0.8	0.4
	R - Fresno	0.1	0.1	0.2	0.8
	S - Stockton/Sacramento	0.2	0.2	0.9	0.4
	T - Coastal Bay Area	0.3	0.3	-0.3	0.7
	V - Humboldt	0.0	0.0	-2.4	0.0
	W - Kern	0.0	0.0	-0.3	0.8
	X - San Jose/Concord	0.3	0.3	1.5	0.1
	Y - Sierras	0.0	0.0	-2.1	0.0
	Z - Sierras	0.0	0.0	-0.3	0.7
Industry Type	11 - Agriculture, Forestry, Fishing and Hunting	0.0	0.0	1.2	0.2
	22 - Utilities	0.0	0.0	-0.4	0.7
	23 - Construction	0.0	0.0	-1.0	0.3
	31 - Manufacturing - Food and finished products	0.0	0.0	-1.0	0.3
	32 - Manufacturing - Primary materials	0.0	0.0	-0.1	0.9
	33 - Manufacturing - Metals and machinery	0.0	0.0	2.6	0.0
	42 - Wholesale Trade	0.0	0.0	-1.3	0.2
	44 - Retail Trade	0.1	0.1	1.5	0.1
	45 - Retail Trade	0.0	0.0	0.3	0.8
	48 - Transportation	0.0	0.0	-0.5	0.7
	49 - Warehousing, Storage and Couriers	0.0	0.0	-0.2	0.9
	51 - Information	0.0	0.0	0.5	0.6
	52 - Finance and Insurance	0.0	0.0	0.3	0.7
	53 - Real Estate and Rental and Leasing	0.1	0.1	0.1	0.9
	54 - Professional, Scientific, and Technical Services	0.0	0.0	1.3	0.2
	55 - Management of Companies and Enterprises	0.0	0.0	-0.7	0.5
	56 - Waste Management and Remediation Services	0.0	0.0	-0.1	0.9
	61 - Educational Services	0.0	0.0	0.4	0.7
	62 - Health Care and Social Assistance	0.0	0.0	0.0	1.0
	71 - Arts, Entertainment, and Recreation	0.0	0.0	1.1	0.3
	72 - Accommodation and Food Services	0.2	0.2	1.0	0.3
	81 - Other Services (except Public Administration)	0.1	0.1	-1.9	0.1

Category	Variable	Treated	Control	t	p>t
	92 - Public Administration	0.0	0.0	-1.5	0.1
	0 - Unclassified or other	0.0	0.0	-0.5	0.7

Appendix B: Medium Business Alternative Propensity Score Matching Methodology

TOU load impacts for medium businesses presented in the main body of the report are not robust to some minor changes in propensity score matching methodology. That is, when we implement a different matching method that is similar to that used in Section 5 of the report but not precisely the same, we find matches that appear to be successful but imply qualitatively different TOU impacts.

The PS matching method used to generate results in this appendix is similar to that which was used in the PY2013 TOU impact assessment. The primary difference between this methodology and that presented in the main report relates to the types of customers that are permitted to serve as controls. In the PY2013 analysis as well as the results presented here, some small customers (A1 customers in PY 2013 terminology) are included in the pool of control candidates for medium (A10) treatment customers. This was done, in part, to address PY2013 data limitations which are not a concern in PY2014. As long as the resulting matches are successful and of a certain quality, then allowing the control candidate pool to be larger in this way should not pose a problem for the analysis.[22]

A secondary difference between the methodology presented here and that used for the main report is the number of customers included in each matching cohort. PS matching is not performed at once for all medium business customers, but is instead segmented according to more specific size categorizations. The results presented here used smaller (in the sense that there are fewer customers included) but more specific segments.[23] There is a trade-off between size and breadth of the candidate pools. A larger candidate pool should improve match results by providing more match options, whereas broader size segments could produce lower quality matches if the size segment is an important factor for the analysis.

The remainder of the PS matching methodology is as described in the main report. The set of explanatory variables includes customer-specific indicators for industry groups, weather stations, and a series of usage characteristics across periods of the day and months of the year. We allow each eligible control customer to serve as the matched control for up to ten different treatment customers, and we require the match to be of a specified quality in order to be considered successful. Table B.1 summarizes the number of customers included in PS matching and those that are successfully matched.

[22] That is, if two customers are well-matched in the pre-TOU period, we have no reason to believe they would not be well-matched in the post-TOU period, regardless of which rate or size category they fall under.

[23] The appendix methodology uses 10 different size segments for PS matching. The report method uses 5 segments.

Table B.1: Medium Business Numbers of Treatment and Control Group Matches (Alternative Matching)

Customer Group	# Eligible for Matching	# of Successful Matches
Treatment	7,402	7,093
Control	20,077	4,092

Relative to the matching in Section 5 of the report, fewer treatment customers are successfully matched (7,093 vs. 7,235) likely due to the more granular size segments used here, and there are more control customers included in the final match set reflecting the addition of small businesses to the candidate pool. The higher control customer count here implies that fewer control customers are matched to more than one treatment customer, which is typically considered a desirable outcome, whereas the loss of 143 treatment customers using this method is not desirable.

Figures B.1 and B.2 mirror those presented in Section 5 of the report. In both graphs, the outer pie slices represent the distribution of treatment customers and the inner pie slices represent the distributions of control customers. Again, it appears that weather stations and industry groups are similarly represented in the matched treatment and control customer sets.

Figure B.1: Medium Business Matches by Weather Station (Alternative Matching)

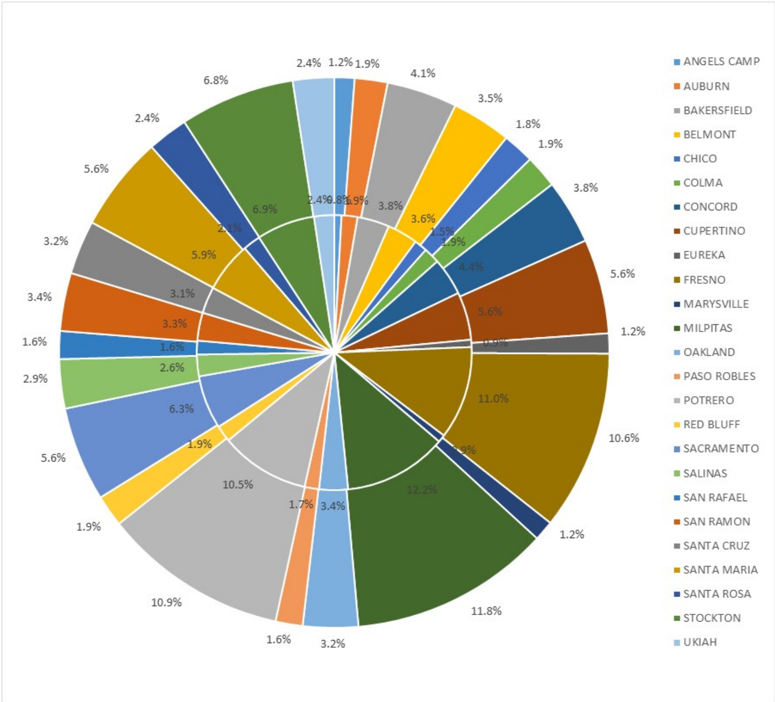


Figure B.2: Medium Business Matches by Industry Group (Alternative Matching)

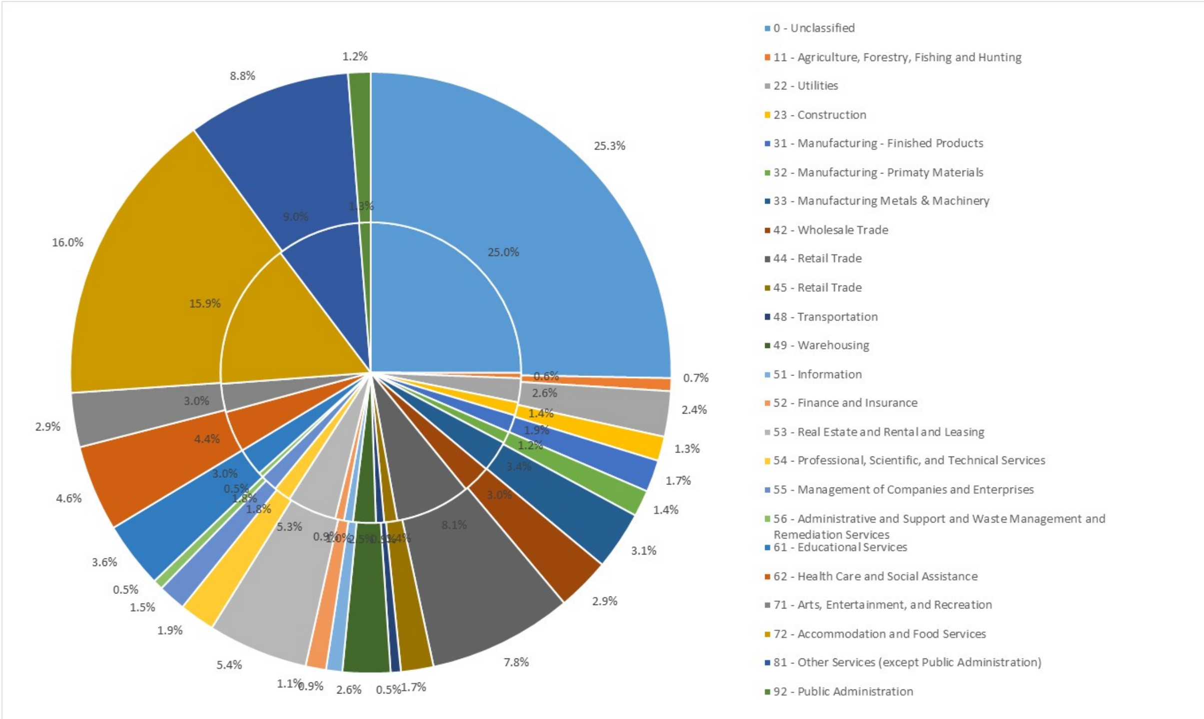


Figure B.3 presents average seasonal load profiles before and after TOU implementation for treatment and matched control customers. The top two graphs are from the pre-TOU period and show that treatment and control loads are well-aligned in 2013, indicating the strength of the matches resulting from this methodology. The correlation between treatment and control profiles is the same here as it was in Section 5 of the report (99.98%), and the average percent deviation across 30-minute increments is closer to zero here (0.2%) than it was using the main report methodology (-0.9%). The bottom two graphs show that load profiles are still well-aligned after TOU implementation, however treatments loads are slightly higher than control loads in both seasons of 2014.

Figure B.3: Medium Business Treatment/Control Load Profile Comparisons (Alternative Matching)

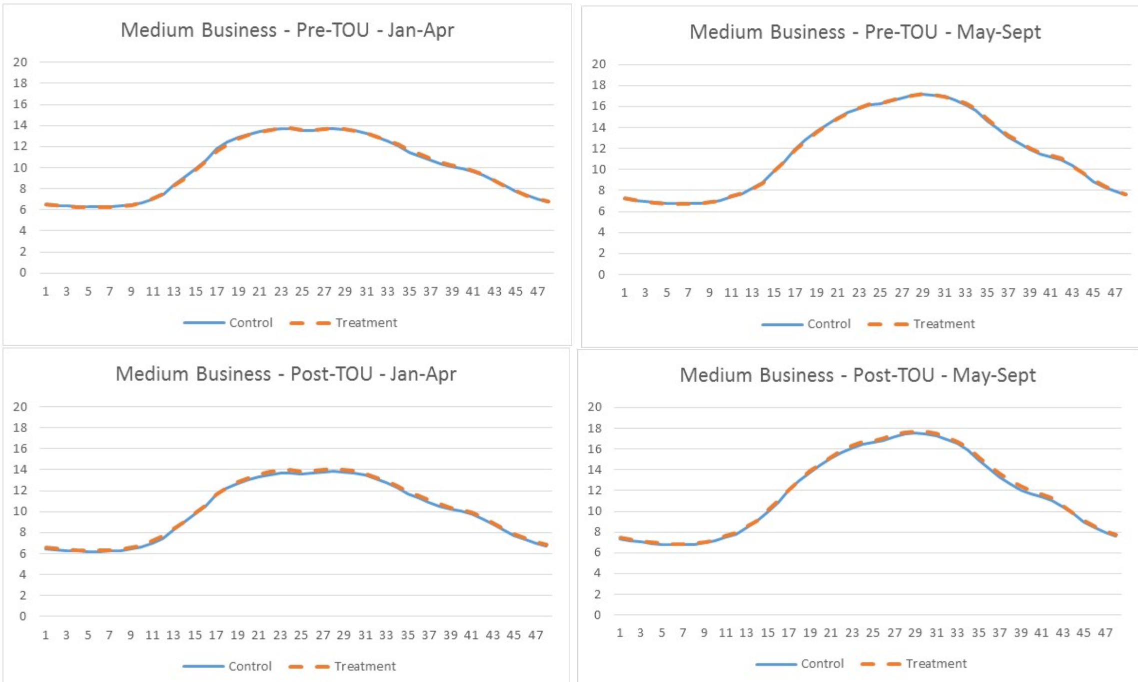


Table B.2 presents simple difference-in-differences calculations using the alternative matching method. The percent impact in the far right column provides an indication of the TOU load impacts we expect to estimate in a formal regression model using these treatment and control customers. Here, the load impacts range from *positive* 1 to 2 percent across seasons and TOU pricing periods, suggesting modest load increases in response to TOU pricing. Table B.3 presents these load impacts along with those from the main report for comparison.

Table B.2: Medium Business Simple Difference-in-Differences Statistics (Alternative Matching)

Rate Type	Day Type	Period	Pre-TOU Transition			Post-TOU Transition			Impact (kW)	% Impact
			TOU	Control	Diff.	TOU	Control	Diff.		
Summer	Weekdays	Peak	16.41	16.34	0.06	16.99	16.77	0.23	0.16	0.98%
		Part Peak	13.30	13.26	0.04	13.72	13.51	0.21	0.16	1.19%
		Off Peak	8.01	8.02	-0.01	8.24	8.13	0.11	0.11	1.40%
	Weekends & Holidays	Off-Peak	9.27	9.20	0.06	9.34	9.17	0.17	0.11	1.21%
Non-Summer	Weekdays	Part Peak	12.29	12.25	0.04	12.44	12.25	0.19	0.15	1.24%
		Off Peak	7.51	7.54	-0.03	7.58	7.46	0.12	0.15	1.98%
	Weekends & Holidays	Off Peak	7.78	7.75	0.04	7.85	7.70	0.15	0.11	1.47%

Table B.3: Medium Business Simple Difference-in-Differences Load Impacts, Main Report Method vs. Alternative Method

TOU Pricing Period			Simple Difference-in-Differences % Impact: Main Report Matching Method	Simple Difference-in-Differences % Impact: Alternative Matching Method
Summer	Weekdays	Peak	-2.2%	1.0%
		Part-Peak	-2.0%	1.2%
		Off-Peak	-2.4%	1.4%
	Weekends & Holidays	Off-Peak	-2.4%	1.2%
Non-Summer	Weekdays	Part-Peak	-3.3%	1.2%
		Off-Peak	-3.5%	2.0%
	Weekends & Holidays	Off-Peak	-3.8%	1.5%

Whereas the PS matching method used in the main report resulted in estimates of load reductions in all seasons and pricing periods, the alternative method presented here implies the opposite.[24] The PS matching methodologies are similar and both appear to provide valid sets of matched treatment and control customers, though we believe the method presented in the report (which matches medium-sized customers only to other medium-sized customers) is perhaps more intuitively appealing. In any case, the sensitivity of the results to the matching method indicates that some caution should be exercised when applying the estimates of medium business load response.

[24] Preliminary formal regression models also estimate hourly load increases in all pricing periods, and the majority of the estimates are statistically significant.