REPORT

2016 Impact Evaluation for San Diego Gas & Electric's Small Commercial and Agricultural Time of Use and Critical Peak Pricing Rates

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1 Executive Summary

SDG&E's implementation of time varying rates was adopted in decision D.12-12-004 and provides a dynamic pricing option to virtually all of SDG&E's 117,000 small commercial and 3,600 agricultural customers (i.e., customers with maximum demand less than 20 kW and customers on agricultural rates). All small business customers where defaulted onto time of use rates (TOU) with a critical peak period (CPP) events, known as TOU-CPP rates. All agricultural customers were defaulted onto time of use rates and offered the option of enrolling on a rate with CPP events.

TOU rates provide a daily signal to customers regarding when electricity production costs are lower or higher and provide them an incentive to reduce or shift their use. On the other hand, CPP prices are designed to reward customers who reduce or shift electricity use from peak hours on a handful of days that drive the need for building additional power infrastructure. In exchange for experiencing higher prices during CPP events, they received rate reductions during non-event days. Both rates provide customers the ability to save by modifying when they use energy.

This report summarizes the 2016 program year (PY2016) demand impacts due to San Diego Gas and Electric's (SDG&E) implementation of time varying pricing tariffs, including:

- Small business TOU (TOU-A)
- Small business TOU-CPP (TOU-A-P)
- Agricultural TOU rates (PATOD, PAT1)
- Agricultural TOU-CPP rates (PACP2, PATODCP2, and PATODPSW)

1.1 2016 Small Business and Agricultural Time-of-Use Impacts

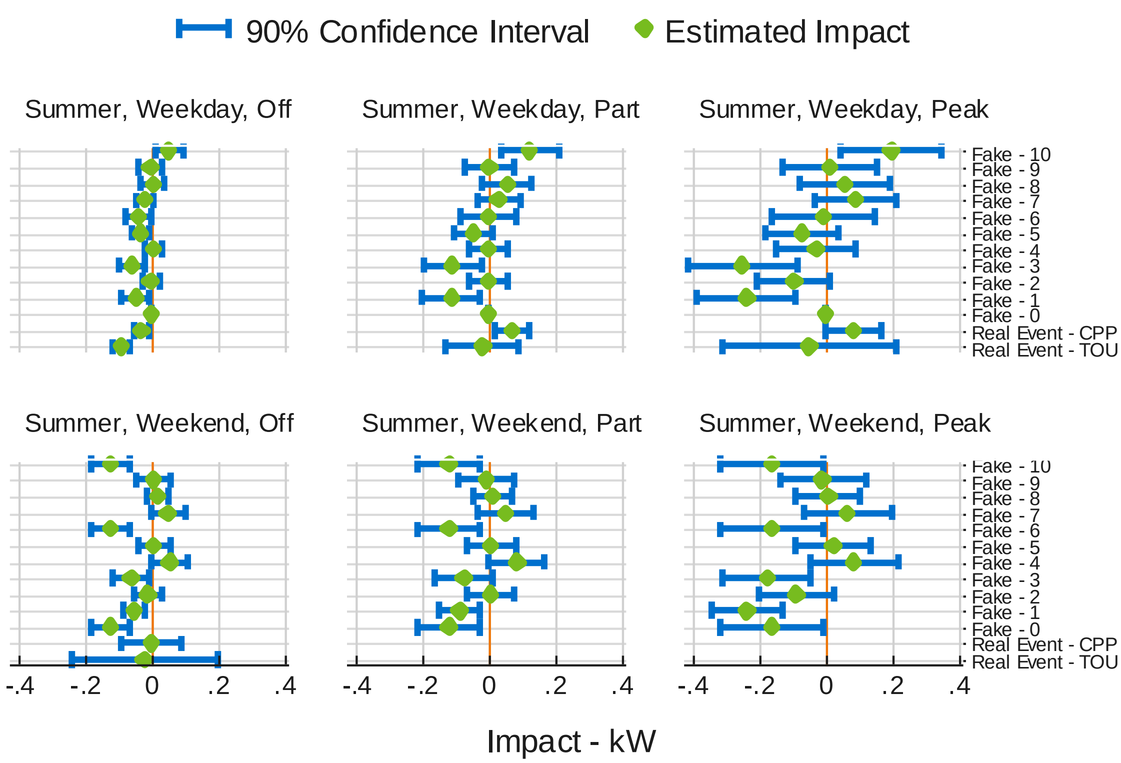
SDG&E scheduled approximately 117,000 small businesses to transition onto default TOU-CPP rates. By end of the 2016 summer, after accounting for business closures, 106,396 (92.8%) remained on the default rate while approximately 8,263 (7.2%) elected to switch to a TOU only rate. Agricultural customers were exposed to a slightly different treatment. Customers on agricultural rates were transitioned over the same period of time as the small commercial customers; however they were defaulted on to a TOU rate without a CPP component. Agricultural customers then had the option to enroll voluntarily in the CPP rate. Of the approximately, 3,950 agricultural customers, over 96% of them remained on the TOU rate and only 141 agricultural customers (4%) enrolled in CPP.

The impacts of the TOU component of rates were estimated by analyzing energy use patterns before and after the implementation of the rates. Electricity use patterns while customers were on non-time varying rates were used to develop the baseline or counterfactual for the time period after the transition to TOU. No viable external control group was available because all small commercial customers were on time varying rates after the transition. This method is sometimes referred to as pre-post analysis or as within-subjects analysis since the customer own electricity use patterns are used to develop the counterfactual.

The pre-post method has significant practical limitations, especially for interventions where the percent change in energy, the signal, is small compared to the underlying variation in the data, the background noise. The approach is entirely dependent on the ability of modeling to explain electricity patterns and thus filter background noise. Importantly, during the time between the pre and post periods, other changes could occur in those businesses that would affect their electricity use patterns. These changes are likely to be unknown to the evaluator (e.g., bars and restaurants shift to LED TV's) and therefore could be misattributed to the TOU rate. Another way to put it is that models that rely on pre-post models assume that, on average, the only difference between the pre and post period is the change in rates and variables included in the model (e.g., weather, day of week, seasonality). The approach is also prone to false precision since the confidence bands may not reflect potential bias due to omitted variables.

Impacts associated with the TOU components of rate of small commercial TOU rates were not statistically significant - that is, impacts, if any, could not be distinguished from random chance. The ex-post load impacts show nearly zero load reductions in response to TOU rates for small commercial customers in all pricing periods. Reductions ranged from slight increases in usage as well as slight decreases, but in all cases failed to meet significance thresholds. The lack of significant findings for TOU impacts does not mean they do not exist, but rather that the design of the implementation and the small effects prevents the evaluation from detecting impacts, if any, without a control group.

Figure 1-1: TOU Impacts by Weekday and Rate Block



In order to assess the degree to which a pre-post method could detect impacts, Nexant implemented a series of placebo tests. The approach consisted of including fake transitions prior to the true treatment and assessing if the models detected an effect when using data from the fake “before” period to estimate the counterfactual for the fake “post” period. Because the transition was fake, a placebo, impacts from TOU were actually zero and any estimated impacts were due to modeling error. Figure 1-1 shows the results from the placebo tests.

To assess the degree to which agricultural customers began to shift their load in response to TOU price signals, Nexant first assessed the change in daily load consumption per rate block. If load shifting is occurring, the percentage of daily consumption in each rate block would change from the pre-transition period to the post-transition period. Table 1-1 shows the result of this analysis. Consumption across periods did not shift substantially; off peak consumption stayed the same, and a slight increase in semi-peak consumption during weekdays, 1.5%, was offset by a slight decrease in weekday on-peak consumption, 1.4%. These shifts, however, are too small to be distinguishable from noise. The regression model impacts associated with agricultural TOU rates were not statistically significant - that is, impacts, if any, could not be distinguished from random chance.

Table 1-1: Agricultural Customer Consumption Shares by Summer Rate Block

Weekday	Rate Block	Avg kW Pre	Avg kW Post	Share Pre	Share Post
Weekend	Off Peak	3.0	2.6	100.0%	100.0%
Weekday	Off Peak	3.3	2.8	31.3%	31.3%
	Semi Peak	3.6	3.1	34.3%	34.8%
	On Peak	3.6	3.1	34.4%	33.9%

1.2 2016 Small Business and Agricultural Critical Peak Impacts

The focus of the CPP event day analysis was on the price response over and above the response to the always on TOU rates.

CPP event day load impacts are typically less challenging to detect than TOU rates for several reasons. The price signal is much larger and, thus, larger percent impacts are expected and easier to isolate from variation in electricity use – i.e., a larger signal to noise ratio. Second, CPP events exhibit an on/off pattern allowing the observation of customer behavior with and without high prices. This is on/off pattern is powerful when multiple events are called and some non-event days resemble event days. Third, it is possible to develop an external control group by identifying customers who have similar electricity use patterns on non-event days. While less ideal than a control group developed through random assignment, matched control group customers experience the same weather and same conditions as CPP customers during event days. Moreover, non-event day differences between control and CPP groups can be removed via the difference-in-differences method.

In 2016, however:

- Small Commercial CPP was brand new in 2016 to a population of customers that were new to both TOU rates and CPP events.
- SDG&E called one CPP event for all of 2016 that was unusual. It was called on Monday, at the end of the summer (September 26), on an extreme temperature day far hotter than any other days in 2016. Because of the timing of the event, business customers were sent notifications on Sunday. The evaluation lacked multiple events and lacked any non-event days with comparable weather.
- There were event notification issues. It was the first live test of large scale event notifications for business customers. Of the customers who signed up for notification, only 25% were sent a notification text message or email prior to the event. This number does not necessarily represent the number of customers who were successfully notified prior to the CPP event due to news alerts.
- The low customer notification rate combined with the timing of the CPP event notification likely contributed to customers' lack of response

To estimate the impact of the CPP event, Nexant utilized two strategies. First, a within-subjects approach was used, where non-CPP days and regression models were used to estimate the counterfactual. This method is viable for event-based programs when multiple events are called and some non-events days approximate temperature experienced during CPP days. The sole event day, however, was highly unusual and was significantly hotter than non-event days. This is why Nexant verified the results of the within-subjects method using a matched control group coupled with difference-in-differences regression model. Matched control groups use non-participants to form the comparison groups.

CPP event day load impacts for small businesses are shown in Table 1-2. Impacts were estimated for a variety of customer segments and sub-segments. Overall, the aggregate results failed to show any significant load impacts across all CPP customers. However, impacts were observable for some of the various customer segments, shown highlighted in green in Table 1-2. Most of the segments that delivered demand reductions either had a large share of customers who opted into the default CPP or had enabling technology.

Table 1-2: CPP Event Load Impacts by Customer Segment

Category	Subcategory	kWh: Load w/o DR	kWh: Impact	kWh: Std. Error	Percent: % Impact	Percent: 90% CI: Lower Bound	Percent: 90% CI: Upper Bound	Avg. Event Temp.
All	All	4.00	0.00	0.08	0.00%	-3.16%	3.16%	97.44
Bins Ann kWh	Decile 1	0.04	0.00	0.00	-5.20%	-11.95%	1.54%	97.21
	Decile 2	0.31	-0.01	0.01	-3.20%	-7.57%	1.17%	97.21
	Decile 3	0.78	-0.01	0.02	-1.16%	-5.72%	3.39%	97.41
	Decile 4	1.29	-0.01	0.03	-0.80%	-5.24%	3.64%	97.45
	Decile 5	2.00	0.00	0.05	-0.21%	-4.71%	4.30%	97.48
	Decile 6	2.86	0.01	0.07	0.34%	-3.86%	4.54%	97.46
	Decile 7	3.94	0.02	0.09	0.48%	-3.40%	4.36%	97.51
	Decile 8	5.52	0.02	0.12	0.32%	-3.18%	3.81%	97.50
	Decile 9	7.86	0.05	0.14	0.68%	-2.34%	3.69%	97.57
	Decile 10	15.40	-0.18	0.27	-1.15%	-4.04%	1.74%	97.59
Coastal	Coastal	3.78	-0.17	0.08	-4.45%	-7.83%	-1.07%	96.20
	Inland	4.12	0.11	0.08	2.63%	-0.77%	6.02%	98.21
Enrollment Cohort	Prior to 2015	1.86	-0.06	0.04	-3.36%	-6.50%	-0.22%	97.71
	JFM15	2.22	-0.21	0.08	-9.40%	-15.41%	-3.39%	97.83
	AMJ15	4.55	-0.07	0.19	-1.50%	-8.34%	5.34%	97.22
	JAS15	5.63	-0.44	0.15	-7.76%	-12.12%	-3.40%	97.10
	OND15	2.97	-0.03	0.05	-1.17%	-3.75%	1.40%	97.32
	JFM16	3.98	0.03	0.08	0.83%	-2.52%	4.18%	97.58
	AMJ16	4.39	-0.02	0.08	-0.34%	-3.23%	2.54%	97.03
Industry	Agriculture, Mining & Construction	3.28	-0.15	0.08	-4.61%	-8.83%	-0.39%	97.11
	Manufacturing	5.83	-0.08	0.11	-1.30%	-4.40%	1.80%	97.92
	Offices, Hotels, Finance, Services	4.42	0.04	0.08	1.01%	-2.06%	4.07%	97.57
	Other or Unknown	2.12	0.00	0.05	-0.13%	-3.99%	3.73%	97.25
	Retail Stores	5.34	0.00	0.10	0.05%	-2.91%	3.01%	97.48
	Schools	4.99	0.14	0.13	2.82%	-1.46%	7.11%	97.22
	Wholesale, Transport & Other Utilities	5.58	-0.36	0.22	-6.53%	-13.06%	-0.01%	97.35
Load Shape	Afternoon Peak	5.20	0.04	0.13	0.73%	-3.35%	4.80%	97.47
	Early Peak	4.83	0.04	0.10	0.86%	-2.62%	4.33%	97.64
	Nearly Flat	3.90	-0.03	0.06	-0.73%	-3.34%	1.89%	97.30
	Night Load	0.99	-0.09	0.04	-9.20%	-15.74%	-2.65%	97.20
	U-Shaped	0.53	-0.06	0.03	-11.61%	-20.87%	-2.34%	97.63
Notification	Not Notified	3.90	0.02	0.07	0.52%	-2.63%	3.66%	97.44
	Notified	88.39	-12.72	8.21	-14.39%	-29.66%	0.88%	97.88
Other DR	[redacted]							
	Other DR: None	3.91	0.01	0.07	0.14%	-3.00%	3.28%	97.45
	SCTD	8.14	-0.46	0.19	-5.66%	-9.45%	-1.88%	97.51
	SS	5.37	-0.02	0.13	-0.35%	-4.36%	3.67%	97.14

On the 2016 event day, 141 agricultural customers were enrolled in CPP out of approximately 3,800 total agricultural customers. Agricultural customers may choose to opt in based on their ability to respond, their aversion to increased event-day prices, or because they are structural winners – that is they already use less load during peak hours and do not need to shift behavior to benefit from the rate. The pre-transition load shapes for agricultural customer enrolled on CPP indicates that customers who opted into CPP already used less load during peak hours. On average, they had daily usage more than ten times the typical agricultural customer and a U-shaped load, with much higher consumption during the early morning and late evening than during peak hours in the middle of the day. Finding matched control groups for these customers proved difficult because they were decidedly unique and lacked similar counterparts that remained on TOU rates. Neither the matched control with difference-in-differences nor the within-subject models indicated impacts that could be distinguished from random chance.

1.3 Key Findings and Recommendations

Key findings from the evaluation include:

- Results from the evaluation of TOU and TOU-CPP rate impacts for small commercial and agricultural customers failed to yield any significant impacts in the 2016 ex post evaluation.
- While impacts were not observable, in aggregate, some small segments delivered reductions. Most of the segments that delivered demand reductions either had a large share of customers who opted into the default CPP or had enabling technology.
- Results of the enrollment analysis indicate that smaller customers tend to opt out at a higher rate than larger customers, and that offices/hotels/financial services customers opt out at a higher rate compared to other industry segments.
- The sole CPP event was unusual. It was called on Monday, at the end of the summer (September 26), on an extreme temperature day far hotter than any other days in 2016. Because of the timing of the event, business customers were sent notifications on Sunday.
- Notification for CPP was poor; only approximately 25% of CPP customers were sent a notification SMS or email prior to the event. This number does not necessarily represent the number of customers who were successfully notified prior to the CPP event.
- The low customer notification rate combined with the timing of the CPP event notification likely contributed to customers' lack of response.
- Calling only one CPP event limits the amount of data available and the ability to draw any meaningful conclusions.
- It is difficult to estimate ex post TOU load impacts unless customers are defaulted onto new rates in periodic stages so there is a meaningful period of time when some customers are on new rates and others are not.
- The lack of significant findings for TOU impacts does not mean they do not exist, but rather that the design of the implementation prevents the evaluation from discovering impacts without a control group.
- Because no ex post impacts were observed, the ex-ante impacts are also zero.

Key recommendations from the evaluation include:

- Test notification systems before the beginning of summer. This can be done using a small, randomly selected set of CPP customer (e.g. 200).
- Implement a series of experiments to increase the understanding of TOU rates. Based on SDG&E's metrics, customers understood that their rate was changing more than they understood the rates themselves, when they had to respond, and how they could do so. Nexant recommends a series of side-by-side small scale tests to assess which methods for informing customer of TOU rates work most effectively, prior to a full roll out to the entire population.
- Implement a series of experiments on how to best improve event notification. If customers are not aware of CPP events on the day of the event, they will not be able to respond. Nexant recommends a series of side-by-side small scale tests to identify the most effective approach, prior to a full roll out to the entire population.

- Call more events but make sure some non-event days are also hot. The on/off nature of CPP events is powerful when multiple events are called and when some non-event days resemble event days. Load impacts for a single, highly unusual CPP day are difficult to detect.
- In future TOU and TOU-CPP implementations, such as the transition of residential customers, hold out a randomly assigned control group. Customer response to TOU rates is difficult to detect without a control group. In specific, Nexant recommends holding out a control group for multiple years into order to assess persistence of impacts and long term price response. We recognize that CPUC decisions may not be clear about the ability to hold out a control group and encourage utilities to explicitly request permission to do so.
- Consider withholding a randomly assigned control group for non-emergency CPP events. All the research shows that impacts for mass market, weather sensitive customers are better detected via a randomly assigned control groups. This approach would entail randomly assigning customer to, for example, 20 groups and dispatching 19 groups but withholding one group to establish the baseline. While ideal for assessing the program impacts, we caution that such procedures can impact other business processes such a billing engines. As a result, the full costs of implementing such a strategy need to be considered.

2 Introduction

A majority of small commercial and agricultural customers across the U.S. pay a flat price and do not have an incentive to consider the pattern of their energy consumption behavior, nor are they aware of the extent to which consumption patterns drive utility energy and infrastructure costs. The transition to TOU-CPP rates was designed to incentivize customers to factor in when they consume, in addition to how much they consume, when considering their bill. Inherently, this leads to a closer alignment between the prices customers face and the cost of supplying power.

2.1 Key Research Questions

Nexant estimated the ex post load impacts for small commercial customers that voluntarily enrolled in TOU and TOU-CPP rates in 2015, as well as customers who were defaulted on to these rates in late 2015 and the first half of 2016. Nexant also attempted to estimate energy increases or decreases occurring on non-event days, persistence of impacts and impacts across different customer segmentation categories including business type, customer size, load shape and geographic location.

The evaluation was expected to address the following research questions regarding the effect of TOU rates on peak demand and consumption levels:

- What is the magnitude of demand reductions from each of the rates during event days (or monthly system peak day for TOU only rates)?
- Do the SPP rates also lead to energy savings (or increases) during non-event days what is the magnitude of demand changes for each rate period?
- Did load impacts grow, decay, or remain constant over the course of the season or year?
- How do impacts vary with temperature, if at all?
- Do reductions vary by business type, customer size, load shape, or geography?
- What steps can be undertaken to improve delivery and performance of SPP rates?
- Are there significant differences between customers who chose to remain on TOU-CPP rates rather than opt out to a TOU-only rate?

Because the findings consistently showed impacts that could not be distinguished from random chance, the analysis focused on identifying if specific segments were price responsive and on identifying steps that could be undertaken to improve price response.

2.2 Implementation of Time Varying Rates

SDG&E's implementation of time varying rates was adopted in decision D-12-12-004 and provides a dynamic pricing option to virtually its entire estimated 117,000 small commercial population (i.e., customers with maximum demand less than 20 kW) as well as over 3,900 agricultural customers who were defaulted on to a base TOU rate. Implementation of time varying rates is a significant shift for SDG&E's smaller customers and provides an incentive for reducing consumption during peak periods as well as an opportunity for customers to save on monthly bills by adjusting their behavior. These rates also better reflect the cost of producing and delivering electricity.

Prior to transitioning all customers to time varying rates in the fall of 2015, SDG&E made the rates available to a selected group of small commercial customers on an opt-in basis before the summer of 2014. Customer eligibility for the opt-in rates was determined based on billing analysis and marketing focused on a group of customers who had account representatives and/or were expected to save money compared to their current flat rate.[1] Of the customers who were marketed to, approximately 2,600 enrolled in either the TOU or TOU-CPP rate by the end of 2015, with a roughly even split between the two rates.

2.2.1 Transition schedule

SDG&E has implemented the rate in two main stages. First, starting in 2014, SDG&E marketed time varying rates exclusively to customers who were expected to experience lower bills. If they enrolled, they did so on a voluntary basis. They were offered a time-of-use (TOU) rate with a preset schedule of prices that vary by season, weekday/weekend and hour of day. In addition, SDG&E offered a similar rate overlaid with a critical peak pricing component (TOU-CPP). With this rate, customers faced a much larger price during critical periods, designed to signal the need for larger reductions. In exchange, customers received a discount during all other hours. Because of the targeted, voluntary enrollment, customers enrolled in time varying prices during the summer of 2015 were not representative of the broader small commercial and agricultural population. This small, voluntary phase was useful for testing enrollment, dispatch, and communication mechanisms, helping identify improvements and refinements for the much larger implementation of default time varying rates.

Starting in November 2015, all small commercial and agricultural accounts transitioned over a six month period to a default CPP rate with an underlying TOU structure (TOU-CPP). Small commercial customers can opt-out to a TOU rate without a critical peak pricing component (TOU-A). Agricultural customers are defaulted on to a TOU rate without a CPP component and instead had the option to opt in to CPP participation. Since May 2016, flat rates have no longer been available to small commercial customers and therefore a control group is not available within the SDG&E territory.

The rollout of default TOU rates was staggered over 6 months starting in November 2015. The rollout groups reflect customers that are systemically different from one another and are not randomly assigned. The groups for the 2016 rollout are in order:

- One account, one premise, and one meter customers expected to experience lower electricity bills without changing their electricity use patterns New customers
- One account, one premise, and one meter customers expected to experience higher electricity bills if they did not change their electricity use patterns
- Accounts with assigned account representatives
- Accounts with multiple meters per premise and/or account

[1] Such customers are sometimes called “structural winners” because the pattern of their existing load shapes would result in monthly bill savings in the absence of any behavioral response to the rate.

2.2.2 TOU and CPP Rates

Table 2-1 describes SDG&E's TOU rate schedule, using examples from TOU-A and TOU-A-P rates from Summer 2016. Figure 2-1 presents the summer weekday schedule visually. By design, the rates are designed to be revenue neutral, meaning that on average customer revenue collected by SDG&E does not change assuming no change in electricity use. To do so, electricity prices are higher than flat prices when electricity is more expensive and lower when electricity costs are lower. The time-varying rates provide customers an incentive to consume power more efficiently and reduce consumption during periods when prices are highest.

Table 2-1: SDG&E Small Commercial TOU and CPP Rate Schedule

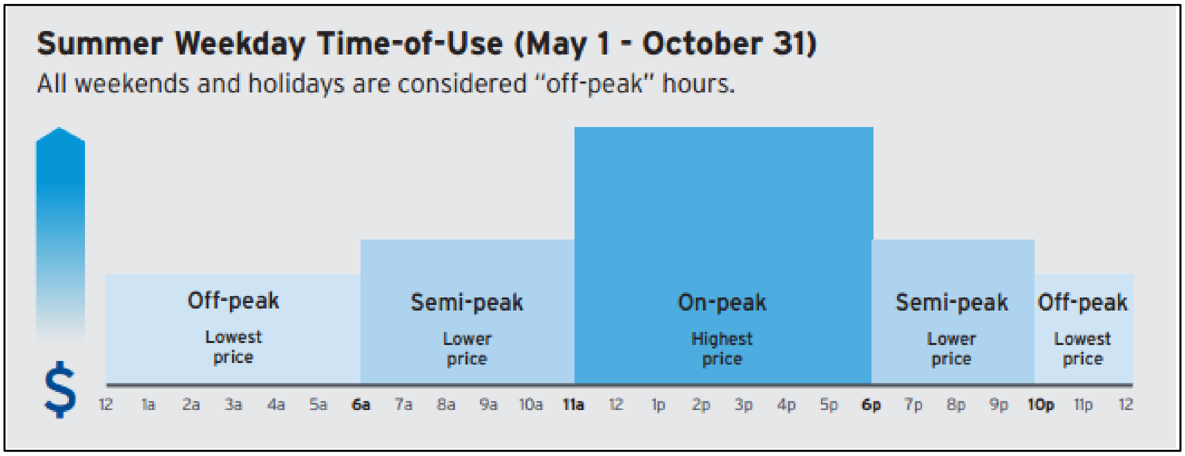
Season	Day Type	Rate Block	Time	CPP	TOU Only
Winter	Weekend	Off Peak	All Day	0.18	0.18
	Weekday	Off Peak	10pm-6am	0.18	0.18
		Semi Peak	6am-5pm 8pm-10pm	0.19	0.19
		On Peak	5pm-8pm	0.21	0.21
		CPP Adder	NA	1.17	NA
Summer	Weekend	Off Peak	All Day	0.18	0.20
	Weekday	Off Peak	10pm-6am	0.18	0.20
		Semi Peak	6am-11am 6pm-10pm	0.21	0.24
		On Peak	11am-6pm	0.23	0.27
		CPP Adder	NA	1.17	NA

Table 2-2: SDG&E Agricultural TOU and CPP Rate Schedule

Season	Day Type	Rate Block	Time	CPP	TOU Only
Winter	Weekend	Off Peak	All Day	0.14	0.13
	Weekday	Off Peak	10pm-6am	0.14	0.13
		Semi Peak	6am-5pm 8pm-10pm	0.16	0.15
		On Peak	5pm-8pm	0.17	0.16
		CPP Adder	NA	1.25	NA
Summer	Weekend	Off Peak	All Day	0.18	0.17
	Weekday	Off Peak	10pm-6am	0.18	0.17
		Semi Peak	6am-11am 6pm-10pm	0.21	0.21
		On Peak	11am-6pm	0.25	0.24
		CPP Adder	NA	1.25	NA

As shown in Tables 2-1 and 2-2, TOU customers experience slightly higher summer peak and semi-peak rates in exchange for not participating in CPP events, while CPP customers receive a discounted peak per-kWh rate but will be charged $1.17 per kWh during CPP events. Peak period prices are higher for both sets of rates than off peak periods, and summer rates are higher than winter rates for all rate blocks. Figure 2-1 illustrates this visually.

Figure 2-1: SDG&E Summer Weekday TOU Schedule



2.3 TOU and CPP Participant Characteristics

Starting in 2014, a small number of small commercial customers began opting in to TOU rates from flat rates. By the end of 2015, approximately 17,000 and 14,600 customers were on TOU and CPP, respectively. Starting in 2016, SDG&E began defaulting customers on to CPP rates in contrast with earlier customers who had opted in. By May 2016, roughly 97% of the total population of small commercial customers had been defaulted to the time-varying rates. By the 2016 event day, there were only approximately 8,263 TOU customers.

Figure 2-2: Enrollment History for TOU and CPP Rates

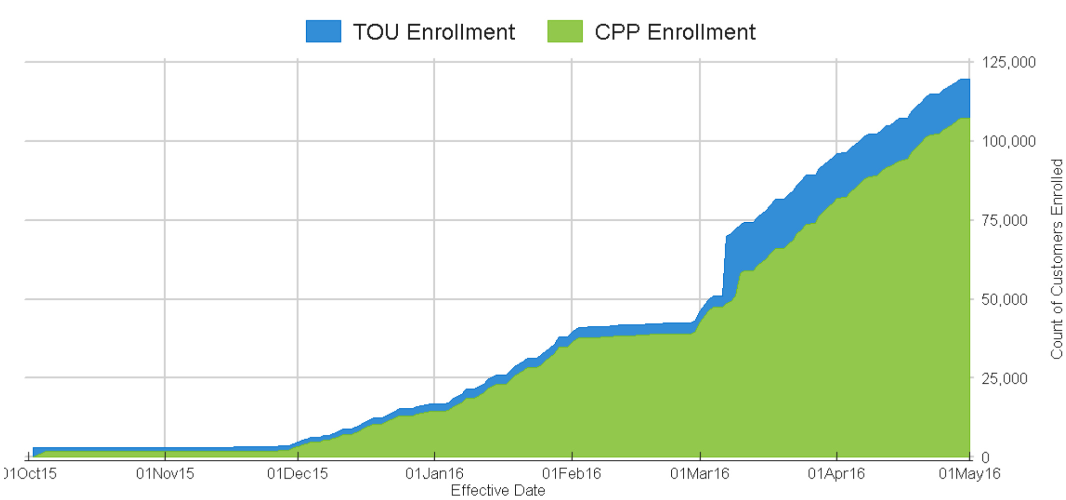


Table 2-3 characterizes the distribution of small commercial and agricultural customers according to different segmentations at the time of the CPP event (September 26, 2016). Ex post impacts for each customer segment shown in Table 2-3 are presented in Table 4-1.

Table 2-3: Distribution of CPP Customer Characteristics

Category	Subcategory	TOU Only Accounts	TOU-CPP Accounts
All	All	8,263	106,396
Deciles of Annual Consumption	Decile 1	970	9,972
	Decile 2	881	10,447
	Decile 3	666	10,883
	Decile 4	686	10,789
	Decile 5	695	10,808
	Decile 6	821	10,748
	Decile 7	822	10,777
	Decile 8	897	10,683
	Decile 9	736	10,837
	Decile 10	1,089	10,452
Climate Zone	Coastal	4,387	40,576
	Inland	3,876	65,820
Enrollment Cohort	AMJ15	2	44
	AMJ16	3,605	21,054
	JAS15	5	75
	JAS16	492	79
	JFM15	3	165
	JFM16	2,841	69,752
	OND15	1,289	12,771
	Prior to 2015	26	2,456
Industry	Agriculture, Mining & Construction	1,190	5,495
	Institutional/Government	1,149	21,925
	Manufacturing	225	4,125
	Offices, Hotels, Finance, Services	2,269	48,406
	Other or Unknown	660	7,942
	Retail Stores	546	10,519
	Schools	225	1,954
	Wholesale, Transport & Other Utilities	1,999	6,030
Load Shape	Afternoon Peak	1,323	23,162
	Early Peak	1,662	22,440
	Nearly Flat	4,466	48,517
	Night Load	131	1,677
	U-Shaped	681	10,600
Notified on CPP Day	Not Notified	8,263	106,284
	Notified	-	26,421
Other DR	CBP	1	11
	Other DR: None	8,033	101,952
	SCTD	113	936
	SS	116	3,497

2.4 Enrollment and CPP Opt-Out Analysis

Small commercial customers were defaulted onto CPP rates in staggered clusters over a 6 month period starting in November 2015. The rollout included a default CPP component, which customers had the option to opt-out of and on to a base TOU rate. Agricultural customers were defaulted onto TOU rates and had the option of opting out onto a CPP rate.

Nexant performed an enrollment analysis for the small commercial customers to identify if particular subsets of customers were more or less likely to opt out of the default CPP rate. Enrollment analyses are particularly important for ex ante impact estimation, as they give an indication of which customers are more likely to remain on a rate going forward. This is important as customers who remain on the CPP rate may have different impacts forecasted than those who opt out. For example, customers who may not be able to reduce usage during CPP events and who would consequently incur economic penalties may opt-out of CPP at higher rates than the average customer. By removing these low performing customers, the performance of the program will improve on average.

Nexant segmented customers by size, industry, region and the percent of the customer’s load used on-peak. Results of the enrollment analysis indicate that smaller customers tend to opt out at a higher rate than larger customers, and that offices/hotels/financial services customers opt out at a higher rate compared to other industry segments. Of interest is the observation that customers with higher percentages on-peak usage opted out at a slightly higher rate than customers with more even load shapes. Intuitively, this seems reasonable as these customers may have less flexibility to shift usage throughout the day and are consequently incentivized to de-enroll from CPP.

2.5 Customer Outreach and Education

Nexant’s evaluation suggests that SDG&E’s processes and procedures for TOU and CPP customer outreach, education and notification could be improved, resulting in better CPP event performance and customer price response to TOU rates. To assist in its evaluation, Nexant requested information related to SDG&E’s customer communication, outreach and education processes. Of particular interest are the following: 1) what was done in terms of notification, education and communication leading up to the rate transition, and 2) what is being done to improve customer communication going forward?

2.5.1 TOU Education and Outreach

An important prerequisite for realizing the benefits from TOU pricing is that customers must be aware they are on such a rate and understand how TOU pricing affects their bills. The transition necessarily involved efforts to ensure customers were aware of the transition, understood TOU pricing conceptually and recognized how the transition would affect them specifically. As part of the transition to TOU rates for small commercial customers, SDG&E implemented a comprehensive outreach and education campaign designed to increase awareness and improve understanding of the new rates.

Nexant reviewed SDG&E’s quarterly regulatory reporting on SPP outreach and education efforts. The remainder of this section summarizes the efforts and activities taken by SDG&E to better inform and engage its small business customers before and during the TOU rate transition. The goal of SDG&E’s

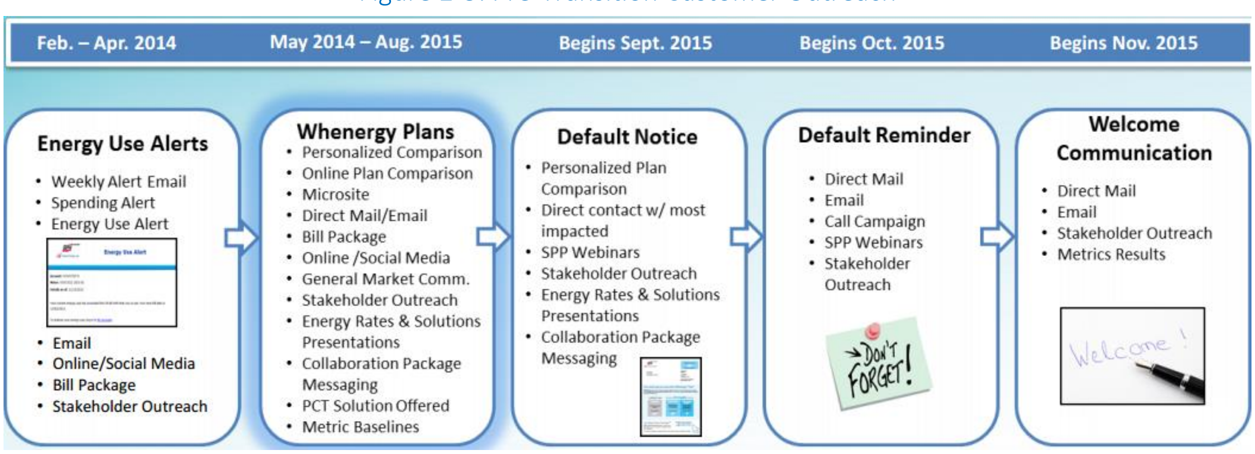
education and outreach efforts was to ensure that customers were prepared to transition to the new pricing and to empower customers to make informed decisions about their energy usage. On their own, education and outreach efforts do not necessarily lead to changes in customer behavior since customers might fully understand TOU rates, but elect to not modify their behavior.

Between November 2015 and April 2016, approximately 117,000 small commercial and agricultural customers were transitioned to TOU pricing plans (with or without a CPP component). During that time, SDG&E developed 21 tailored customer journeys to create a more personalized experience throughout the rate transition, and conducted a proactive outbound calling campaign to approximately 16,000 customers, including all customers having a projected bill impact of greater than 2%.

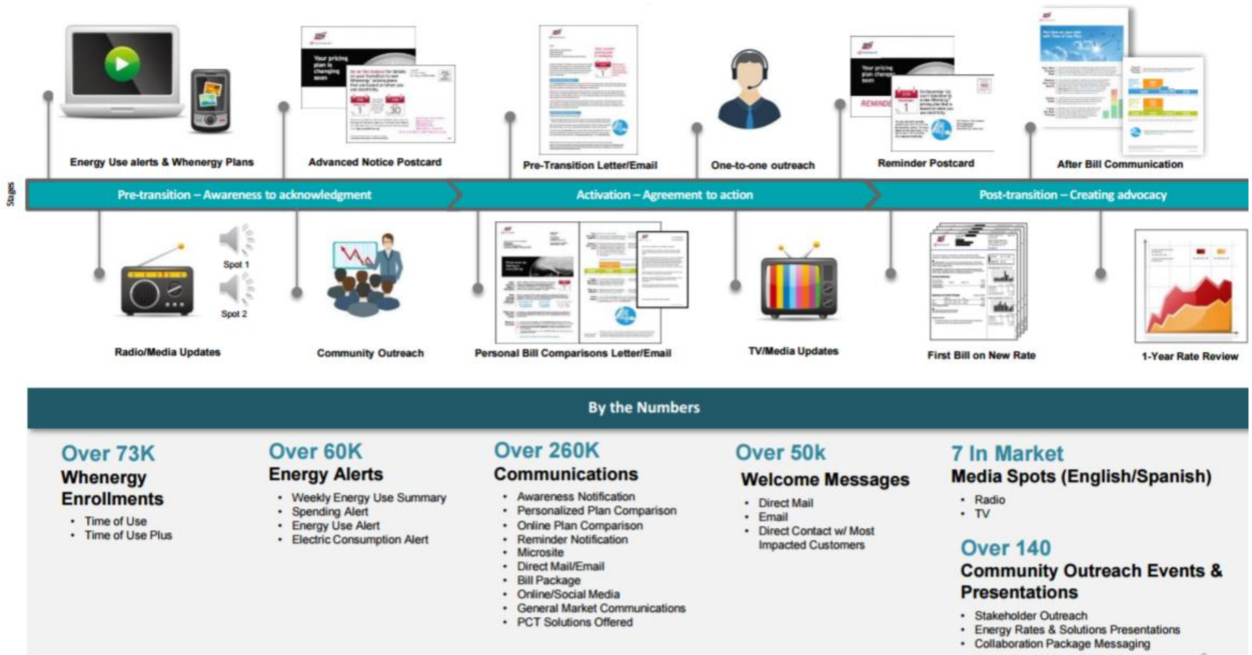
SDG&E's pre-transition outreach and education plan included a series of communications directed to small business customers via a variety of mediums.

- Energy Use Alerts were sent via e-mail between February and April 2014. Alerts included weekly energy use summaries and regular notices of electric consumption and spending levels.
- During the period May 2014 through August 2015, SDG&E conducted a Whenergy Plan campaign, where personalized plan comparisons were developed for individual customers and communicated via direct mail, e-mail and personalized online websites. Plans provided price comparisons between customers' existing plans and the new TOU and TOU-P plans.
- Default transition notices were sent beginning in September 2015 and included personalized plan comparisons and opportunities to participate in educational SPP webinars and energy rates presentations. SDG&E made specific efforts to directly contact customers who were most affected by the transition.
- Default transition reminders were sent beginning in October 2015. Reminders were sent via direct mail, e-mail and call campaigns, and included additional opportunities for customers to take part in educational SPP webinars and presentations.
- Welcome messages were sent to customers beginning in November 2015 upon transition to the new TOU rates. Welcome messages were sent via direct mail and e-mail.

Figure 2-3: Pre-Transition Customer Outreach

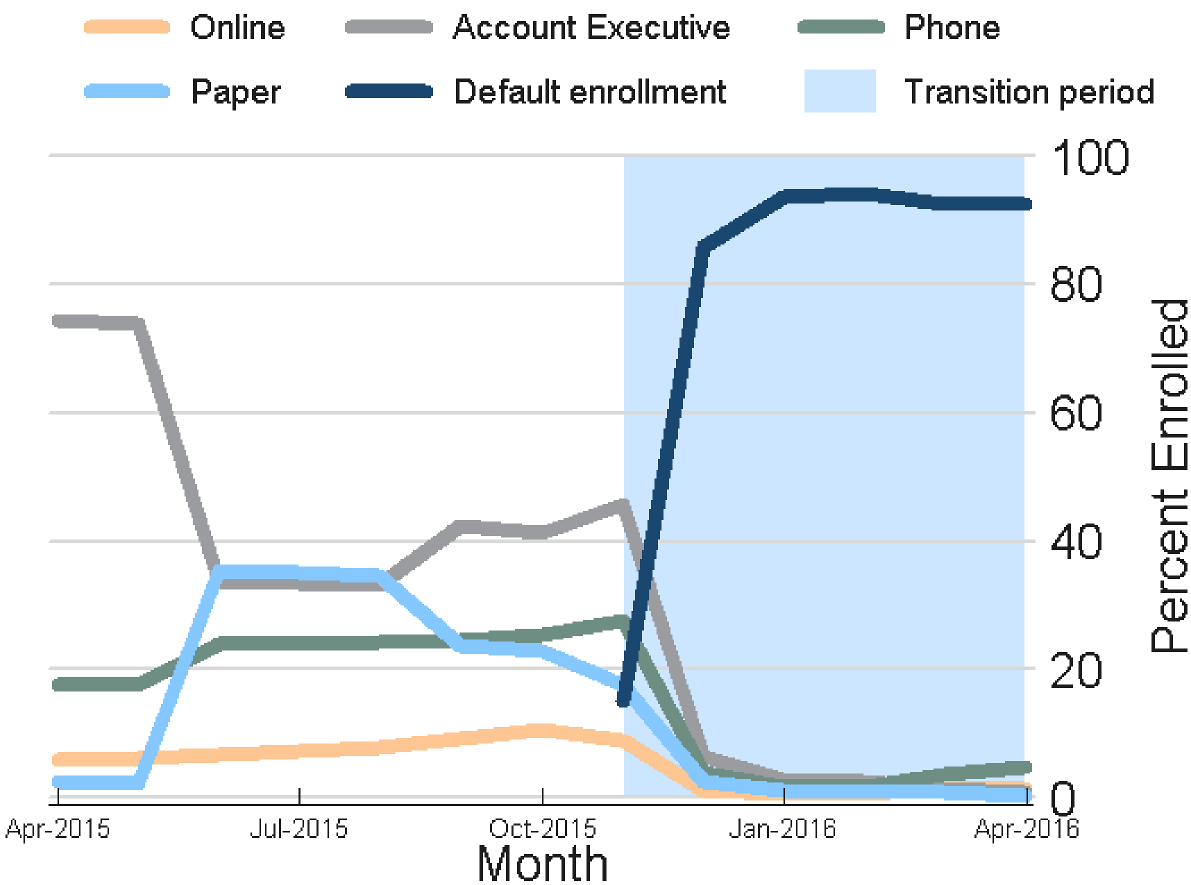


Pre-transition customer outreach and education efforts included both general and targeted communication channels. General channels included an online website, a TOU fact sheet, utility bill inserts and TV and radio media spots. Targeted outreach included personalized plan comparison reports, delivered via direct mail and e-mail. Advanced notice postcards were sent to small business customers in September and October 2015 and reminder postcards were sent approximately two weeks before their TOU pricing transition became effective.



Prior to the default transition period beginning in November 2015, customers were able to opt-in to the TOU rates on their own accord. Opt-in rates are a function of effective customer outreach. Prior to November 2015, customers were able to enroll in TOU pricing via direct marketing, over the phone, online or through an account executive. Figure 2-4 shows monthly enrollment rates by channel.

Figure 2-4: Enrollment Mechanism for TOU by Month



To assess the effectiveness of mandatory TOU education and outreach efforts, SDG&E conducted customer surveys on a regular basis prior to, during, and after the transition. The objectives of the survey were to gain insight into how many business customers had heard of TOU pricing and were aware that they would be auto-enrolled beginning in late 2015, understand how customers perceive TOU pricing will impact their bills, and gain a sense of what information would be most helpful to customers in preparing for TOU pricing. A baseline survey was sent out prior to the roll out of opt-in TOU and CPP rates to establish an understanding of how familiar small commercial and agricultural customers were with the concept of TOU and CPP programs. Customers continued to be surveyed regularly during the transition. Selected results of those surveys are shown below.

Metric	Baseline	Pre-Transition (May 2015)	Post-Transition (September 2016)
Customers are aware of Time of Use and CPP rates	4%	42%	64%
Customers knew they may need to manage their electricity use differently on CPP event days or on TOU. Customers understand that the reduction of the peak is dependent on customer actions on very few	30%	23%	57%

specific days and times.			
Customers understand that there are peak hours during the day when demand for electricity is the greatest and the cost of providing electricity is more expensive.	39%	37%	61%

In general, customers became more familiar with the TOU and CPP implementation over time. As the survey method changed between the baseline and the pre- and post-transition surveys, the baseline results are not directly comparable to the later results. However, across all three metrics of awareness, customers improved between May 2015 and September 2016. While this generally indicates that customers were more aware of the transition as time went on, the interpretation of these results is highly dependent on the form of the survey and the pool of survey participants. These results should be considered as a part of the education and outreach materials and not necessarily as representative of the full population due to transition to these new rates.

In addition to the direct customer outreach and education activities described above, SDG&E engaged populations through a variety of industry stakeholder outreach and engagement events. Table 2-4 summarizes SDG&E's stakeholder outreach and engagement events from September 2015 through November 2016.

Table 2-4: Stakeholder Outreach & Engagement Activities

Month-Year	Event/Activity Name	Outreach Tactic
Sep-15	Whenergy Promotions	Messaging and promotion through 60 Chamber, Business and Trade Associations
	San Clemente Chamber Lunch & Learn	Presentation of Energy4Biz, SMB rate changes
	Carlsbad Business Expo	Booth with SMB, Energy4Biz collateral
	Oceanside Chamber of Commerce Lunch & Learn	Presentation of Energy4Biz, SMB rate changes, locational EE
	SD Regional Chamber Small Business Awards	Booth with SMB, Energy4Biz collateral
Oct-15	Breweries Business Seminar	Presentation of Energy4Biz, SMB rate changes
	Trade Professional Forum	Presentation of Energy4Biz, SMB rate changes
	Vista Business Expo	Booth with SMB, Energy4Biz collateral
Nov-15	Fall Greenhouse Grower & Farmer Conference	Booth with SMB, Energy4Biz collateral
	Restaurant/Kitchen Equipment Event	Presentation of Energy4Biz, SMB rate changes
	SYSCO Quarterly All Hands Meeting	Presentation of restaurants and related vendors on Energy4Biz, SMB rate changes
Dec-15	Whenergy Promotions	Messaging and promotion through 60 Chamber, Business and Trade Associations
	Restaurant Survival Workshop Sysco	Presentation of Energy4Biz, SMB rate changes
Jan-16	SMB Rollout Update	Updated 24 Chambers of Commerce on SMB Rollout Activities
	Chula Vista Small Busines Seminar	Booth with SMB, Energy4Biz collateral

	Food & Beverage Association Board Meeting	Update on SMB Rollout Activities
Feb-16	California Restaurant Association Board Meeting	Update on SMB Rollout Activities
	Neighborhood Market Association Annual Exhibition	Booth with SMB, Energy4Biz collateral
	BOMA San Diego Energy and Sustainability Committee	Update on SMB Rollout Activities
Mar-16	Whenergy Promotions	Messaging and promotion through 60 Chamber, Business and Trade Associations
	Carlsbad Sustainability Committee	Update on SMB Rollout Activities
Apr-16	IFMA Educational Seminar	Update on SMB Rollout Activities
	BOMA Energy & Sustainability Committee	Update on SMB Rollout Activities
	Food & Beverage Association Board Meeting	Update on SMB Rollout Activities
May-16	Port of San Diego Ship Repair Association	Update on SMB Rollout Activities
	IFMA Membership Meeting	Booth with SMB, Energy4Biz collateral
	BIOCOM Facility Managers Meeting	Update on SMB Rollout Activities
Jun-16	Whenergy Promotions	Messaging and promotion through 60 Chamber, Business and Trade Associations
	Business Improvement District Executive Board Meeting	Update on SMB Activities
Jul-16	California Restaurant Association Board Meeting	Update on SMB Activities and Whenergy
	Latino Business Circle	Update on IDSM and SMB Activities
	San Diego County Farm Bureau General Membership Meeting	Update on SMB Activities
Aug-16	Energy Upgrade California Session	Update on SMB Activities
	Chula Vista Trade Show and Business Mixer	Booth with SMB, Energy4Biz collateral
Sep-16	Whenergy Promotions	Messaging and promotion through 60 Chamber, Business and Trade Associations
	US Green Business Council Seminar	Update on SMB Activities
Oct-16	Industrial Environmental Association Annual Conference	Update on SMB Activities
	Poway Chamber of Commerce Business Expo	Booth with SMB, Energy4Biz collateral
Nov-16	San Diego County Farm Bureau Farm Expo	Booth with SMB, Energy4Biz collateral
	City of Solana Beach Climate Action Plan Workshop	Booth with SMB, Energy4Biz collateral

2.5.2 CPP Event Notification

A limited number, roughly 25%, of small commercial CPP customers received notification in advance of the CPP event. Notification is essential for establishing response to an event-based program, as customers are not likely to modify behavior without knowing that an event is scheduled to take place.

Structural challenges as well as the peculiarity of the event day hampered notification efforts in the following ways:

- Customer-specific notification for CPP was done on an opt-in basis, rather than as default. Customers who were defaulted on to the CPP rate had to sign up to receive notification prior to an event, and only approximately 25% of customers enrolled in notification.
- Active CPP events are shown on SDG&E's website for customers who may not have received email or SMS notification. News media also alerted all customers in SDG&E's territory to the extreme heat on the event day; however this was not specifically targeted at CPP customers and could have also been seen by customers not on the CPP rate, such as customers in the control group.
- Customers were notified between 8:00 and 10:00 pm on the Sunday night before the Monday morning event, meaning that for small commercial customers may not have had time to adjust to the coming event.
- Improving efforts to communicate CPP event will likely lead to greater ability to detect meaningful impacts.

2.6 Study Challenges and Limitations

A number of inherent challenges exist when estimating impacts for TOU and CPP rate responses, in addition to specific challenges related to SDG&E's implementation and outreach practices. In general, two challenges exist which limit the ability of evaluators to identify program impacts:

1. Implementation challenges, such as lack of customer notification or education, reduce the size of the expected impacts

2. Evaluation challenges, where the experimental design limits the ability to detect impacts.

While implementation challenges have been addressed in the previous section, this section discusses the various challenges associated with the impact evaluation of the small commercial rates.

2.6.1 Challenges in Estimating TOU Price Response

Evaluating the impact of TOU rates is intrinsically more complex than evaluating event-based programs and rates. The key challenge is one of attribution. Did the introduction of TOU rates cause a decrease in electricity consumption during peak periods when prices were higher or can the differences in peak period electricity use be explained by other factors? To infer that TOU prices changed electricity use patterns, one must be able to systematically eliminate plausible alternative explanations for differences in electricity use patterns, including random chance.

The best approach for evaluating TOU rates meets the following conditions: 1) random assignment of customers to TOU rates vs. flat rates (producing a control group); 2) obtain pre- and post-TOU transition data; 3) relatively large sample sizes and/or larger price differentials; and 4) apply the study over a period of multiple years. A control group provides information about how TOU participants would have used electricity had they not been exposed to time-varying price signals (i.e. the counterfactual). However, on its own, the use of a control group does not guarantee accurate results. Random assignment helps ensure that the only systematic difference between the two groups is the fact that one group was exposed to TOU prices while the other group was not. Pre-enrollment data allows for verification that the differences in load shapes were indeed caused by the introduction of TOU and were not pre-existing. Large sample sizes and strong price differentials help to reduce the likelihood that observed differences are due to random chance. Finally, a long-term study provides a better understanding of the short- and long-term effect of TOU rates.

However, evaluations of TOU rates are often difficult due to several inherent factors. First, TOU rates are not event based. Once a customer is enrolled on a TOU rate, it is not possible to observe their behavior absent time varying prices since the rate affects customers on a daily basis. As a result, factors that coincide with the pre-enrollment or post-enrollment period and affect electricity use can be misattributed to TOU rates.

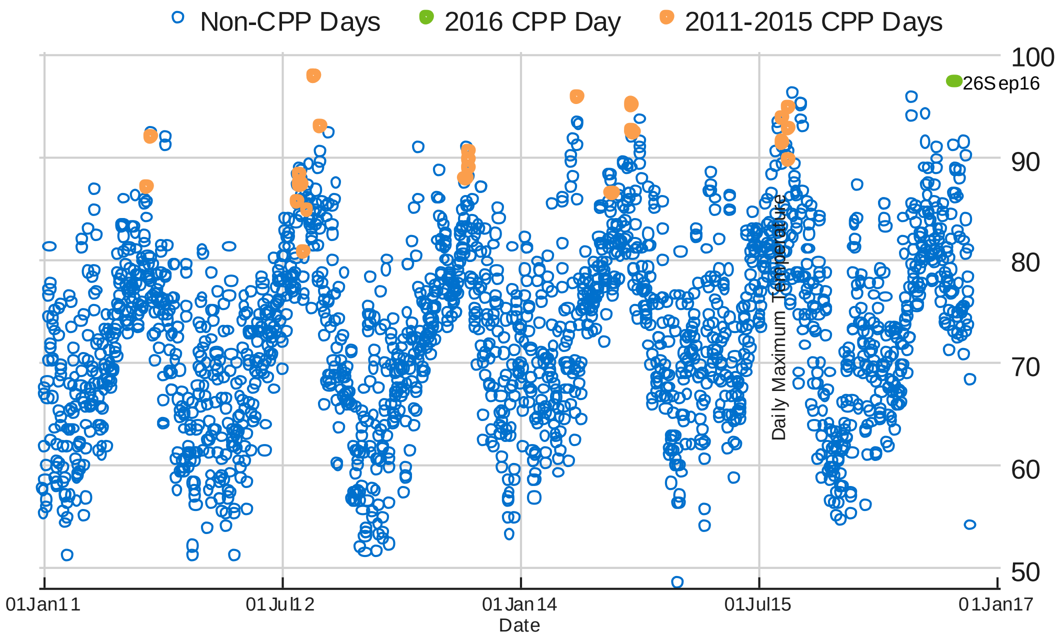
Second, customers often self-select onto the rate or study. For most TOU rates and pricing pilots, customers who agree to enroll are characteristically different from those who are offered participation but decline. This is referred to as a selection effect. These differences might be easily observed or they might be completely unobservable. Comparing electricity use and load shapes for enrollees with those from a random group of customers who were not offered enrollment or, worse, with a group of customers who were offered enrollment but declined, can lead to incorrect conclusions. This challenge was particularly relevant for the 2015 evaluation, when a non-TOU control pool was available, while the program remained an opt-in pilot. Conversely, in 2016 minimal selection effect was present and instead the challenge was the lack of a comparable non-TOU control pool.

Finally, TOU prices are less concentrated, leading to weaker price signals and smaller effects that are more difficult to detect. Smaller percent reductions are harder to distinguish from normal variations in electricity use. Unless relatively large sample sizes are used, it is often difficult to eliminate the likelihood that observed differences are due to chance.

2.6.2 Challenges in Estimating CPP Impacts

While limited customer notification was the predominant issue in the evaluation of the CPP events for small commercial customers, the limited number of events called also hampered evaluation. Only one CPP event was called in September 2016, during an uncharacteristically warm day, late in the summer season, on a Monday. As shown in Figure 2-5, the event day, based on daily maximum temperature, was the hottest since 2012, as well as considerably later in the season than the average event. The event day followed two other hot days, leading to considerable heat buildup in the weekend prior to the Monday event. Calling only one CPP event, especially one on such an unusual day, limits the amount of data available. Unusual weather conditions and seasonal affects may also encourage atypical customer behavior, meaning that the data that is collected is not indicative of the program’s potential going forward. With only one unusual event day, the evaluator’s ability to draw any meaningful conclusions about the response of small commercial customers to critical peak pricing is limited.

Figure 2-5: History of SDG&E's CPP Event Days



2.7 Report Organization

The remainder of this report is divided into six additional sections. Section 3 summarizes study design and methodology, including enrollment and treatment timing of small commercial customers as well as impact estimation methodologies for CPP events and TOU rates schedules. Sections 4 and 5 presents the evaluation's estimated load impacts for the 2016 critical peak pricing (CPP) event and TOU pricing, respectively. Section 6 discusses the inherent challenges associated with calculating ex ante impacts in this case, due to the small ex post impacts shown by the evaluation. Finally, the report ends with conclusions and recommendations, which are presented in Section 7.

3 Evaluation Design and Methodology

To estimate load impacts, it is necessary to estimate what energy consumption would have been in the absence of TOU and CPP-TOU rates—the counterfactual or reference load. To infer that TOU prices changed electricity use patterns, one must be able to systematically eliminate plausible alternative explanations for differences in electricity use patterns, including random chance.

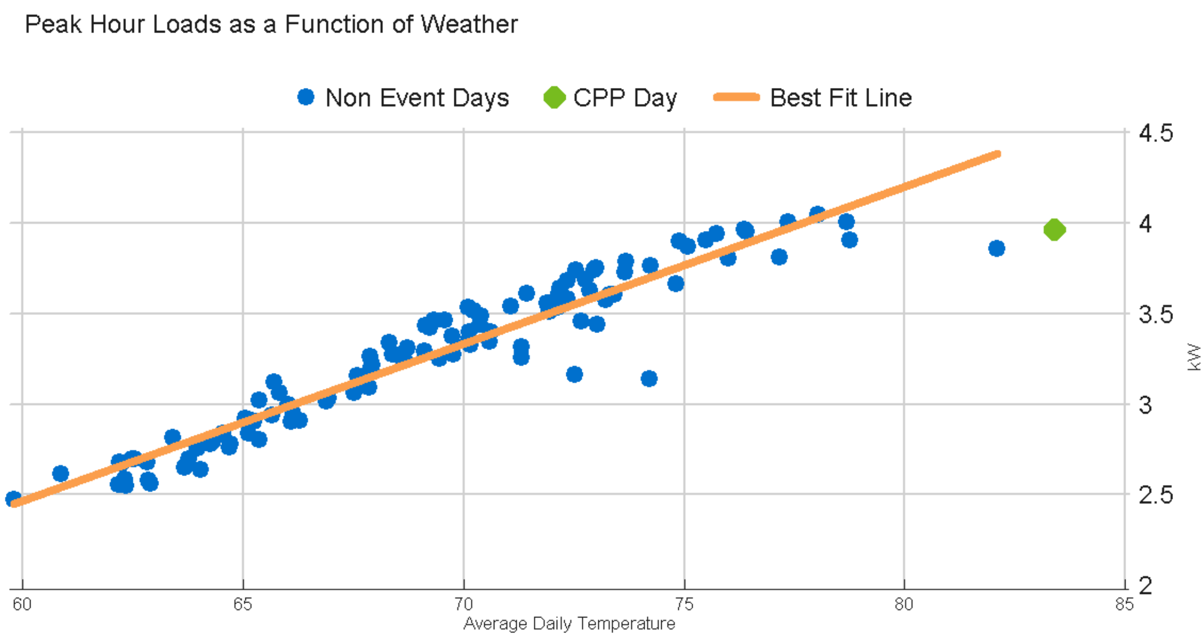
In general, an estimate of the effect of the TOU rate implementation and CPP events can be accomplished in two ways: without or without an external control group. Methods that rely on a customer's own electricity use patterns to develop the counterfactual are sometimes referred to as pre-post analysis or as within-subjects analysis. As discussed previously, Nexant opted to conduct a within-subjects analysis due to the lack of a viable control group. The within-subjects method has significant practical limitations; namely that during the time between the pre and post periods, other changes could occur in those businesses that would affect their demand. These changes are likely to be unknown to the evaluator, such as change in the businesses' operating hours, and therefore could be misattributed to the effect of the TOU rate. Another way to put it, is that models that rely on pre-post models assume that, on average, the only difference between the pre and post period is the change in rates and variables included in the model (e.g., weather). With customer data from 2013 through 2016, there are likely to be material differences in electricity demand profiles within a single customer over that time period.

3.1 Impact Estimation Methodology for CPP Events

For event-based impact estimation, it is common to rely on the use of a control group to observe the counterfactual load. While there was a group of base TOU customers not on the CPP rate during the CPP event, the group was small and not randomly assigned. Without random assignment there may be differences between the treatment group and the opt-out group that could limit the similarity in behavior between the treatment group and opt-out customers. This, in turn, prevents the opt-out group from acting as a true counterfactual. Instead, Nexant used regression analysis to model the relationship between weather and demand on non-event days in order to establish what customer energy use patterns would have been absent curtailments on event days. This approach works because the intervention is introduced on some days and not on others, making it possible to observe loads patterns with and without the program treatment. This enables the evaluator to assess whether the outcome – electricity use – rises or falls with the presence or absence of CPP. This approach hinges on having comparable non-CPP days. When all of the hottest days are CPP days, the counterfactual is based on extrapolating trends beyond the range of non-event temperatures, producing less accurate and less reliable impact estimates for the hottest days. While the September 26th CPP day was the hottest day of the summer, as well as the SDG&E system peak day, there were several other hot non-event days that were available to act as proxy days.

Figure 3-1 illustrates the underlying concept of the regression approach using SDG&E data. The blue circles reflect the individual non-CPP weekdays and the orange line shows the trend between peak hour loads and weather. The green diamond shows the load during CPP conditions on September 26. The regression modeling calculates the demand reduction as the difference between the estimated loads absent CPP pricing and the actual loads during CPP conditions. The below example is simplified for illustration purposes. In practice, regression modeling typically includes other explanatory variables besides weather, such as day-of-week effects and/or seasonal or monthly effects.

Figure 3-1: Illustration of Within Subject Regression Model



The process for model selection relied on out-of-sample placebo tests. Nexant defined 10 distinct model specifications and ran each of the 10 models using non-event data. The regression model is used to predict electricity use on a placebo event day – an out-of-sample prediction. Nexant repeated the process for multiple placebo event days and recorded the actual and predicted loads for each day. The out-of-sample predictions are compared to actual electricity use observed on that day, which is used to calculate metrics for bias and precision. The best model is identified by first narrowing the candidate models to the three with least bias and then selecting the model with the highest precision. Finally, the best performing model is used to estimate the counterfactual for actual event days.

Figure 3-2: Out of Sample Model Validation and Selection

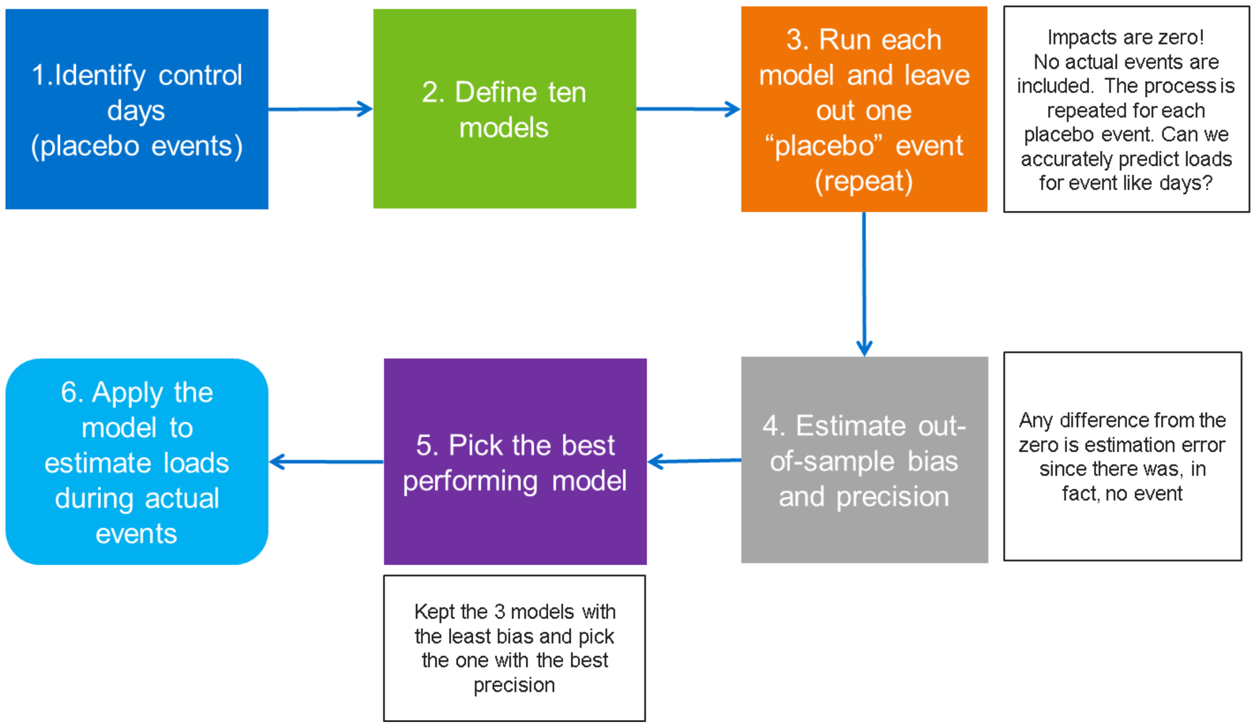


Table 3-1 summarizes metrics for bias and precision.[2] Table 3-2 summarizes the results for each model tested. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error was describes the relative magnitude and direction of the bias. A negative value indicates a tendency to under predict and a positive value indicates a tendency to over predict. This tendency is best measured using multiple days. The precision metrics describe the magnitude of errors for individual events days and are always positive. The closer they are to zero, the more precise the results. The mean percentage error was used to narrow down to the three models with the least bias. The CV(RMSE) metric was used to identify the most precise and final model among the remaining candidates. The best performing model (#5) incorporated both the temperature during the time period and the temperatures throughout the day.

Table 3-1: Definition of Bias and Precision Metrics

Type of Metric	Metric	Description	Mathematical Expression
Bias	Average Error	Absolute error, on average	$AE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$
	Mean Percentage Error (MPE)	Indicates the percentage by which the measurement, on average, over or underestimates the true demand reduction.	$MPE = \frac{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)}{\bar{y}}$

2 Bias is also referred to as accuracy. Precision is sometimes called goodness-of-fit.

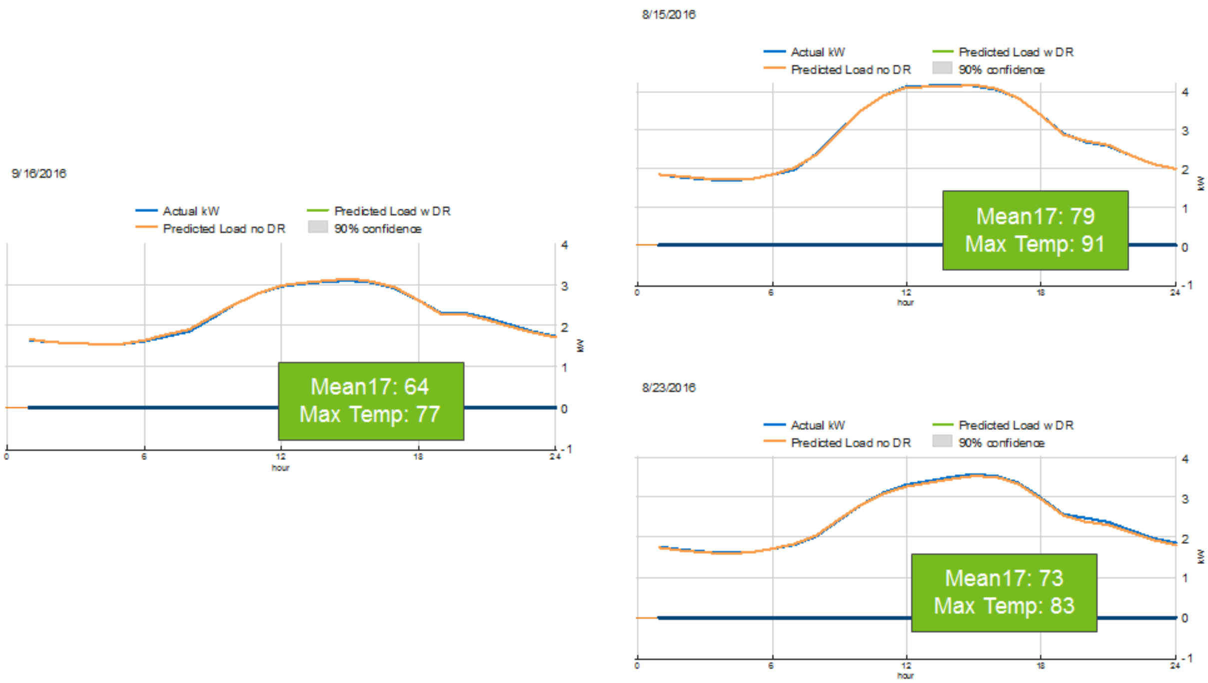
Precision	Root mean squared error	Measures how close the results are to the actual answer in absolute terms, penalizes large errors more heavily	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$
	CV(RMSE)	Measures the relative magnitude of errors across event days, regardless of positive or negative direction. It can be though us as the typical percent error, but with heavy penalties for large errors.	$CV(RMSE) = \frac{RMSE}{\bar{y}}$

Table 3-2: Out of Sample Bias and Precision Metrics for Each Model Tested

Model	Variables	Bias		Precision	
		Avg. Error	Mean Percent Error	Root Mean Squared Error	Normalized RMSE
1	- Pre-event load (9-10am) - Cooling degree hours (Base 70F) - Day of week and month	0.013	0.46%	0.052	1.89%
2	- Pre-event load (9-10am) - Cooling degree hours (Base 65F) - Day of week and month	-0.017	-0.62%	0.081	2.93%
3	- Pre-event load (9-10am) - Maximum temperature for day - Day of week and month	-0.006	-0.20%	0.062	2.24%
4	- Pre-event load (9-10am) - Avg. temperature in prior 24 hours - Day of week and month	-0.026	-0.92%	0.103	3.71%
5	- Pre-event load (9-10am) - CDH and CDD - Day of week and month	0.005	0.16%	0.046	1.64%
6	- Pre-event load (9-10am) - Avg. Temperature in prior 24hr and current CDH - Day of week and month	0.012	0.44%	0.049	1.78%
7	- Pre-event load (9-10am) - Avg. CDH in prior 6 hours and current CDH - Day of week and month	0.011	0.40%	0.053	1.91%
8	- Pre-event load (9-10am) - Avg. CDH in prior 12 hours and current CDH - Day of week and month	0.012	0.44%	0.047	1.70%
9	- Pre-event load (9-10am) - Avg. CDH in prior 18 hours and current CDH - Day of week and month	0.013	0.46%	0.050	1.81%
10	- Pre-event load (9-10am) - Avg. CDH in prior 24 hours and current CDH - Day of week and month	0.012	0.44%	0.049	1.78%

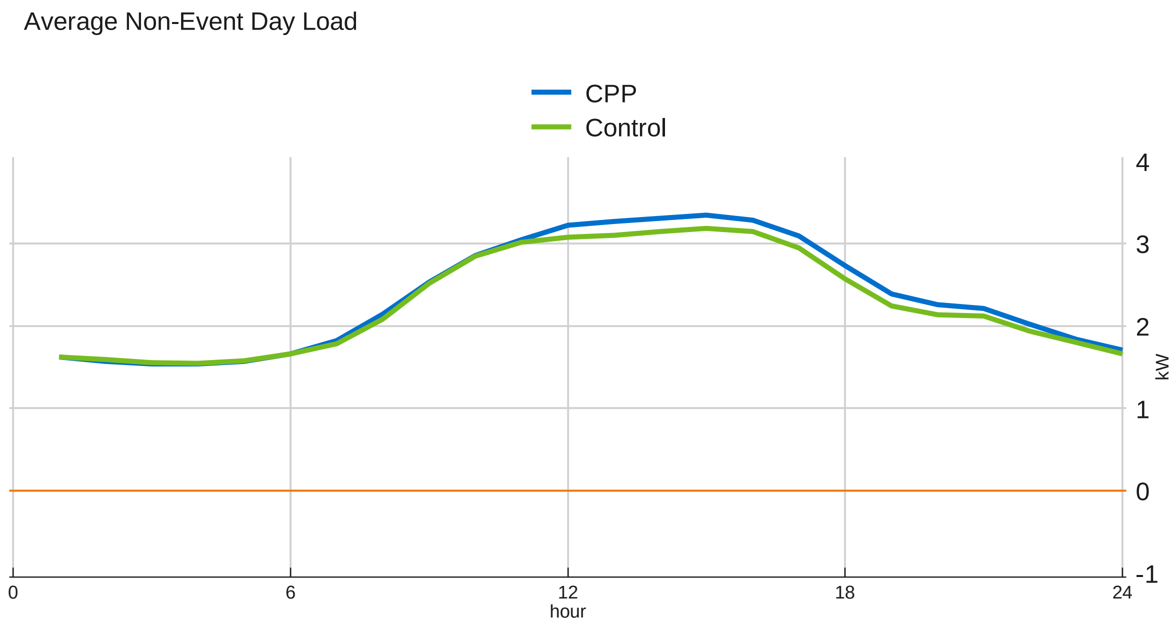
Nexant then tested the validity of the selected model specification and found that the final model does very well at predicting loads across a range of temperature conditions. Figure 3-3 illustrates the alignment between predicted and actual loads for three non-event days with varying temperature conditions. The predictions shown in Figure 3-3 are based on model #5 (outlined in blue) from Table 3-2.

Figure 3-3: Model Load Predictions on Non-Event Days using Model 5



A matched control group was also developed to identify whether impacts could be identified when a control group, that experiences the same weather conditions as the participants, is compared to the CPP customers. The benefit of a control group is that, when selected properly, they provide an estimate of the counterfactual loads without having to extrapolate the relationship between conditions on non-event days and the event day, which may not be valid. The selection of a control group, however, can be challenging in cases where customers are not randomly assigned to the control group. In the case of assessing small commercial CPP impacts, customers who opted out of default CPP may be materially different than customers who remain on the CPP rate. Any underlying differences in how a customer behaves when exposed to event conditions may ultimately be captured in their loads, leading to selection bias in the impacts. To overcome this, attention must be paid to the similarity of participant and non-participant loads on non event days. Shown in Figure 3-4 are the results of the matching. In both magnitude and load shape, the control group customers are very similar to the profile of the CPP customers.

Figure 3-4: Matched Control Group Loads on the Average Summer Non-Event Weekday



3.2 Impact Estimation Methodology for TOU Rate

Because the TOU transition waves were done in non-random customer groupings, Nexant had reason to believe that each wave would have varying observable and unobservable characteristics that would affect their response to the new rate structure. As no viable control group was available within the SDG&E small commercial population to provide an estimate of the counterfactual demand after the transition to TOU rates, Nexant considered several alternate methods to estimate the impact of the transition to time-varying rates, and determined that the best available approach was to use a within-subjects methodology, where pre-transition usage data was used to estimate the post-transition period, normalized by weather and day variables. This method is straightforward, requiring standard evaluation data and well-established methods. However, this approach involves an inherent risk of bias as it assumes that nothing within each customer's business changed over three years of pre and post period data, except weather and the implementation of TOU rates. Additionally, there is a risk that small impacts may be lost in the noise, where variability within each of the pre and post periods eclipses the effect of the TOU rates.

To estimate load impacts, it is necessary to estimate what energy consumption would have been in the absence of TOU and CPP-TOU rates—the counterfactual or reference load. The key challenge of evaluation is attribution. Did the introduction of TOU and CPP-TOU rates cause a decrease in electricity consumption during peak periods when prices were higher or can the differences in peak period electricity use be explained by other factors? To infer that TOU prices changed electricity use patterns, one must be able to systematically eliminate plausible alternative explanations for differences in electricity use patterns, including random chance.

In general, an estimate of the effect of the TOU rate implementation can be accomplished in two ways; either by comparing the pre- and post-period usage of customers who were defaulted on to the rate, known as a within-subjects estimate, or comparing usage of the defaulted customers to a group of customers who are not subject to treatment, or a control group method. Impacts can be evaluated with both pre and post period data and a control group of customers who did not experience a change in rates. While both can be used to develop impact estimate, the within-subjects method has significant practical limitations; namely that during the time between the pre and post periods, other changes could occur in those businesses that would affect their demand. These changes are likely to be unknown to the evaluator, such as change in the businesses' operating hours, and therefore could be misattributed to the effect of the TOU rate Another way to put it, is that models that rely on pre-post models assume that, on average, the only difference between the pre and post period is the change in rates and variables included in the model (e.g., weather) With customer data from 2013 through 2016, there are likely to be material differences in electricity demand profiles within a single customer over that time period.

While control group (or nonparticipant group) methods for evaluating the effect of a TOU rate are preferred, the significant challenge is finding good quality control group that is representative of what the treatment customers would have done in the absence of the TOU implementation. The representative nature of the control group is critical, since that assumption implies that any unobserved changes happening in the treatment group are likely to be happening in the control group as well, reducing the chance that a change is misattributed to treatment. SDG&E did not withhold a random subset of customers from the implementation of default TOU rates during the 2015-2016 transition, meaning that any remaining customers on the flat rate are likely to be different in behavior from the treatment customers in significant ways.

As an alternative method for evaluating the impacts of TOU rates on SDG&E's SMB customer population to mitigate the issues raised above, Nexant opted for a within-subjects approach. Nexant aggregated the interval data of all customers who transitioned to the TOU rate between October 2015 and May 2016 and performed a regression analysis to identify differences in the pre and post period usage. Aggregating the interval data has the advantage of reducing random noise at the individual customer's usage level, making it easier to distinguish small impacts from random fluctuations.

To assess the risk of false precision, Nexant conducted a series of false experiments on the TOU data. False experiments involve setting an artificial transition date for the pre-TOU transition aggregated data, and performing a regression to determine the ability of a model to detect changes of the magnitude expected. As no treatment was introduced during this period, the expected impact associated with the false treatment indicator should be zero. However, the width of the confidence bands surrounding the estimate is of particular interest in these false experiments, as they reflect the underlying variability of the data. In the case where the estimated impact of the true TOU rate transition falls within the confidence bands of the false experiment estimates, one cannot say anything about the significance of that impact. Said another way, even if the estimated impact of the true TOU transition is significant, if it falls within the range of the confidence intervals of the false experiment estimates, the result is false significance. The data and chosen model simply have too much variability to distinguish an impact of that magnitude from noise. To this end, Nexant tested a variety of model specifications in addition to running false experiments for each model. The model specifications are shown in Figure 3-5, with the winning model, highlighted in blue, shown

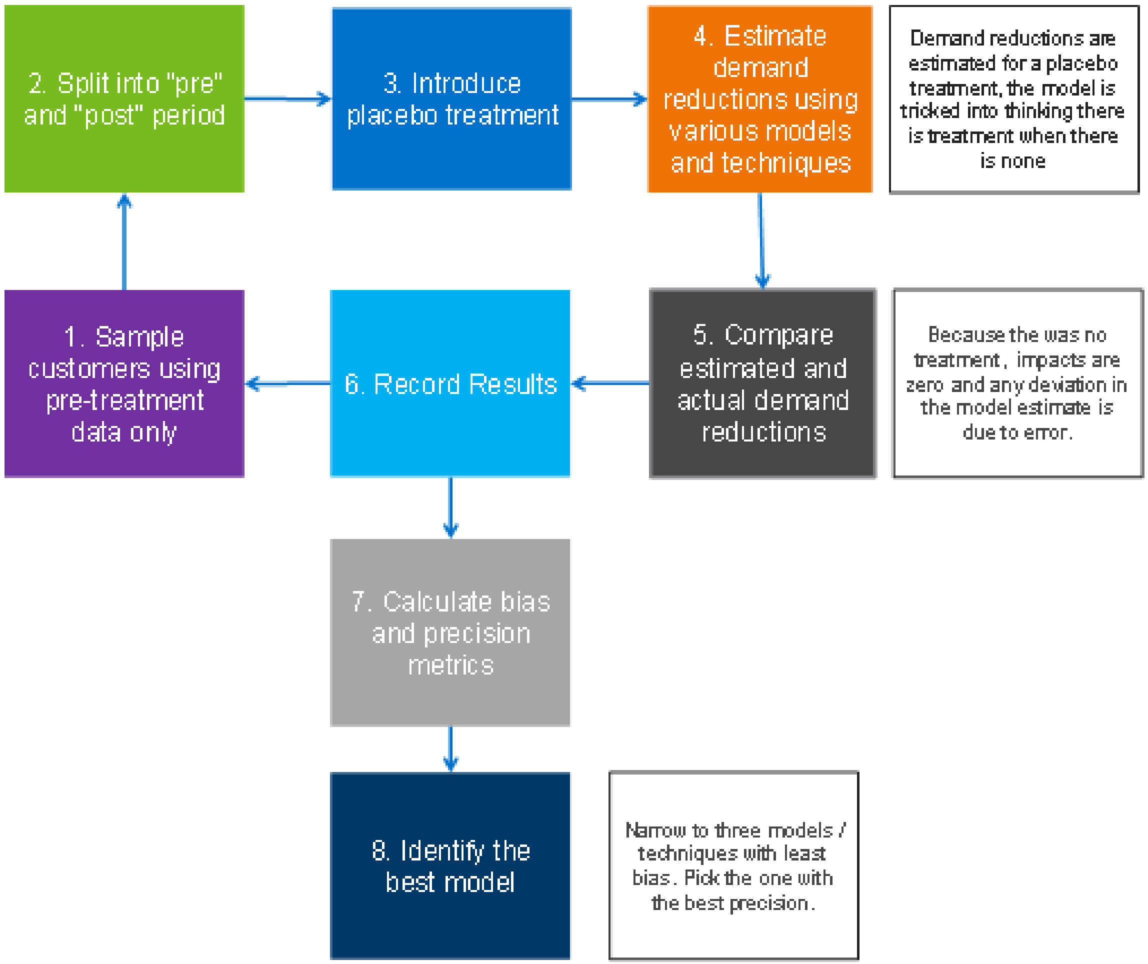
Figure 3-5: TOU Model Specifications Tested

Variables Included	Model Number									
	1	2	3	4	5	6	7	8	9	10
CDD (base)		65			65					
CDH (base)	70				70	70	70	70	70	70
CDH Lag							6hr	12hr	18hr	24hr
Max Temp										
Avg Temp										
Avg Temp Lag					24hr					
Day of Week										
Month & Year										

In each cell, green highlighting indicates that the variable in question was included in the regression. Details within each cell indicate the temperature base used or the number of hours included for variables that captured moving averages.

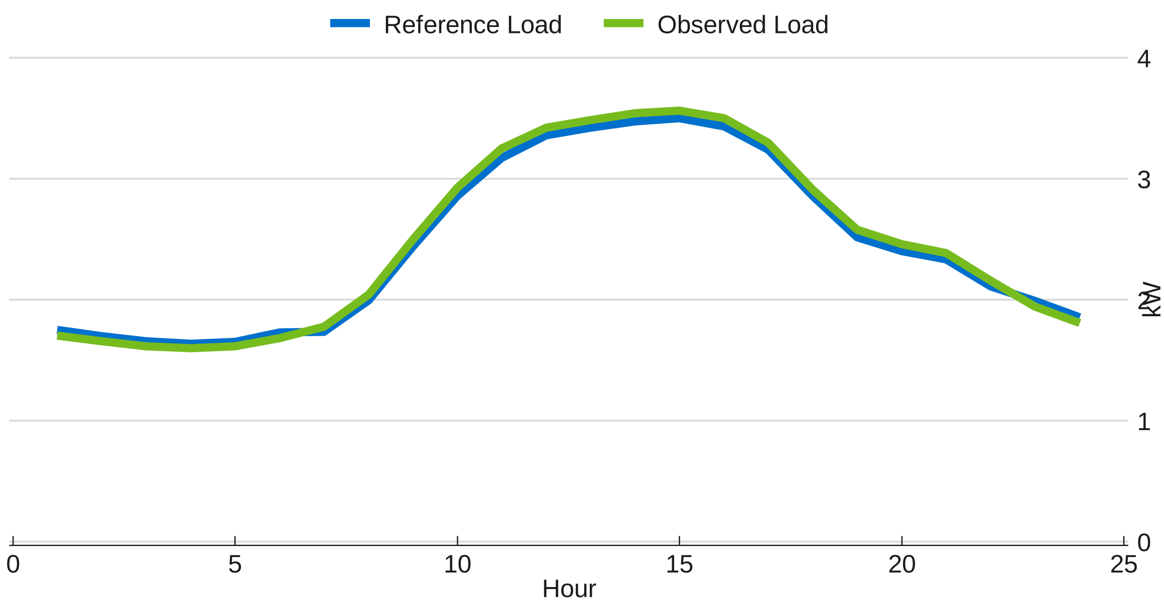
Figure 3-6 summarizes the approach for assessing accuracy and precision of models and techniques. The objective is to test different evaluation methods and models with different samples of participants in order to identify the most accurate analysis method. Reference load accuracy is assessed by introducing placebo treatments, simulating a pre and post TOU period and event days. Because no treatment took place, impacts are zero and any deviation in the model estimate is due to error.

Figure 3-6: Process for Identifying the Best Performing Technique/Model



The results of the pre-transition model selection are shown in Figure 3-7. While the model fit looks extremely good, this simultaneously demonstrates the concern about false precision that is addressed through the use of placebo tests. By running multiple false experiments where an artificial transition date is set, the limits on the ability of the model to determine significant impacts are shown.

Figure 3-7: Pre-TOU Summer Weekday Load using Model 10



4 CPP Ex Post Load Impact Estimates

4.1 Small Commercial CPP Results

When evaluating impacts associated with CPP rates, Nexant analyzed only data for customers who have transitioned to the TOU-CPP rate by May 1, 2016 and excluded all customers who opted on to the TOU-only rate. The analysis showed that almost zero CPP load impacts were achieved for the average customer. One factor driving the low CPP impacts is poor event notification. Only 25% of customers were notified of the CPP event.

Nexant analyzed CPP impacts for a variety of customer segments. Table 4-1 presents average CPP load impacts and percent impacts for several different cohorts within seven categories:

- Customer deciles based on average pre-treatment annual kwh
- Coastal region, determined by climate zone (i.e. coastal vs. inland)
- Enrollment cohorts, subset by the 3-month period in which the customer opted in or was defaulted.
- Industry / sector
- Daily load shape
- Whether the customer received notification for the CPP event
- Dual enrollment in other demand response programs.

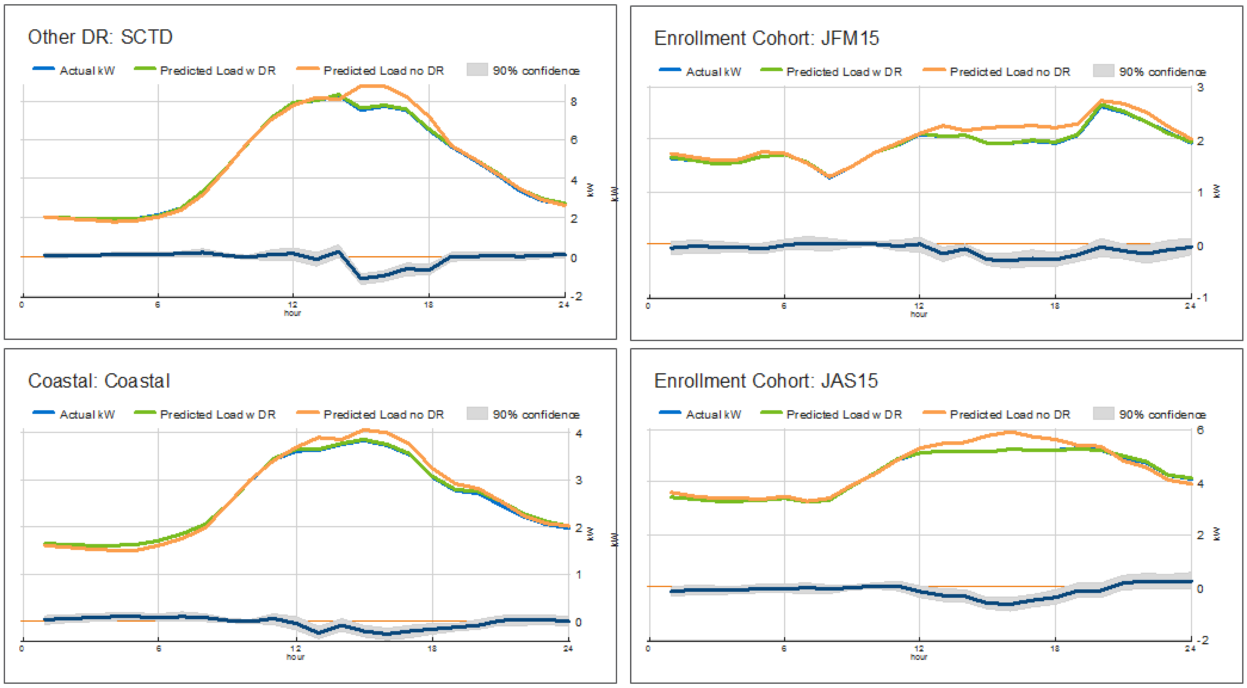
As a whole, even within each category, individual groups showed little or no impacts, with a few groups showing negative impacts (increased demand).

Table 4-1: Average Customer CPP Load Impacts and Percent Impacts

Category	Subcategory	kWh			Percent			
		Load w/o DR	Impact	Std. Error	% Impact	90% CI: Lower Bound	90% CI: Upper Bound	Avg. Event Temp.
All	All	4.00	0.00	0.08	0.00%	-3.16%	3.16%	97.44
Bins Ann kWh	Decile 1	0.04	0.00	0.00	-5.20%	-11.95%	1.54%	97.21
	Decile 2	0.31	-0.01	0.01	-3.20%	-7.57%	1.17%	97.21
	Decile 3	0.78	-0.01	0.02	-1.16%	-5.72%	3.39%	97.41
	Decile 4	1.29	-0.01	0.03	-0.80%	-5.24%	3.64%	97.45
	Decile 5	2.00	0.00	0.05	-0.21%	-4.71%	4.30%	97.48
	Decile 6	2.86	0.01	0.07	0.34%	-3.86%	4.54%	97.46
	Decile 7	3.94	0.02	0.09	0.48%	-3.40%	4.36%	97.51
	Decile 8	5.52	0.02	0.12	0.32%	-3.18%	3.81%	97.50
	Decile 9	7.86	0.05	0.14	0.68%	-2.34%	3.69%	97.57
	Decile 10	15.40	-0.18	0.27	-1.15%	-4.04%	1.74%	97.59
Coastal	Coastal	3.78	-0.17	0.08	-4.45%	-7.83%	-1.07%	96.20
	Inland	4.12	0.11	0.08	2.63%	-0.77%	6.02%	98.21
Enrollment Cohort	Prior to 2015	1.86	-0.06	0.04	-3.36%	-6.50%	-0.22%	97.71
	JFM15	2.22	-0.21	0.08	-9.40%	-15.41%	-3.39%	97.83
	AMJ15	4.55	-0.07	0.19	-1.50%	-8.34%	5.34%	97.22
	JAS15	5.63	-0.44	0.15	-7.76%	-12.12%	-3.40%	97.10
	OND15	2.97	-0.03	0.05	-1.17%	-3.75%	1.40%	97.32
	JFM16	3.98	0.03	0.08	0.83%	-2.52%	4.18%	97.58
	AMJ16	4.39	-0.02	0.08	-0.34%	-3.23%	2.54%	97.03
Industry	Agriculture, Mining & Construction	3.28	-0.15	0.08	-4.61%	-8.83%	-0.39%	97.11
	Manufacturing	5.83	-0.08	0.11	-1.30%	-4.40%	1.80%	97.92
	Offices, Hotels, Finance, Services	4.42	0.04	0.08	1.01%	-2.06%	4.07%	97.57
	Other or Unknown	2.12	0.00	0.05	-0.13%	-3.99%	3.73%	97.25
	Retail Stores	5.34	0.00	0.10	0.05%	-2.91%	3.01%	97.48
	Schools	4.99	0.14	0.13	2.82%	-1.46%	7.11%	97.22
	Wholesale, Transport & Other Utilities	5.58	-0.36	0.22	-6.53%	-13.06%	-0.01%	97.35
Load Shape	Afternoon Peak	5.20	0.04	0.13	0.73%	-3.35%	4.80%	97.47
	Early Peak	4.83	0.04	0.10	0.86%	-2.62%	4.33%	97.64
	Nearly Flat	3.90	-0.03	0.06	-0.73%	-3.34%	1.89%	97.30
	Night Load	0.99	-0.09	0.04	-9.20%	-15.74%	-2.65%	97.20
	U-Shaped	0.53	-0.06	0.03	-11.61%	-20.87%	-2.34%	97.63
Notification	Not Notified	3.90	0.02	0.07	0.52%	-2.63%	3.66%	97.44
	Notified	88.39	-12.72	8.21	-14.39%	-29.66%	0.88%	97.88
Other DR	[redacted]							
	Other DR: None	3.91	0.01	0.07	0.14%	-3.00%	3.28%	97.45
	SCTD	8.14	-0.46	0.19	-5.66%	-9.45%	-1.88%	97.51
	SS	5.37	-0.02	0.13	-0.35%	-4.36%	3.67%	97.14

Some customer categories, however, did achieve modest impacts. Figure 4-1 shows CPP load impacts that were achieved by four distinct customer subcategories highlighted in Table 4-1. Of particular note are customers dually enrolled in SCTD, where demand response is enabled by the provision of a programmable communicating thermostat. These customers showed significant impacts while the devices were set to respond to the event. Customers enrolled between January and March 2015 as well as those who enrolled between July and September 2015 also showed statistically significant impacts. These customers were part of the opt-in pilot rather than defaulted, suggesting that opt-in customers were more likely to respond to an event than customers who were defaulted. Opt in customers were also more likely to have notification methods in place, meaning they were more likely to be aware of the event than the rest of the CPP population.

Figure 4-1: CPP Load Impacts Achieved in Certain Customer Categories



In addition, calling only one CPP event day limits the amount of data available and the ability to draw any meaningful conclusions. While several other categories showed statistically significant impacts, this doesn't necessarily imply that the load reductions observed were directly attributable to the CPP event. With a 95% confidence interval, observations that meet statistical significance thresholds may still be due to random chance 5% of the time.

Figure 4-2: Average Customer CPP Load Impacts

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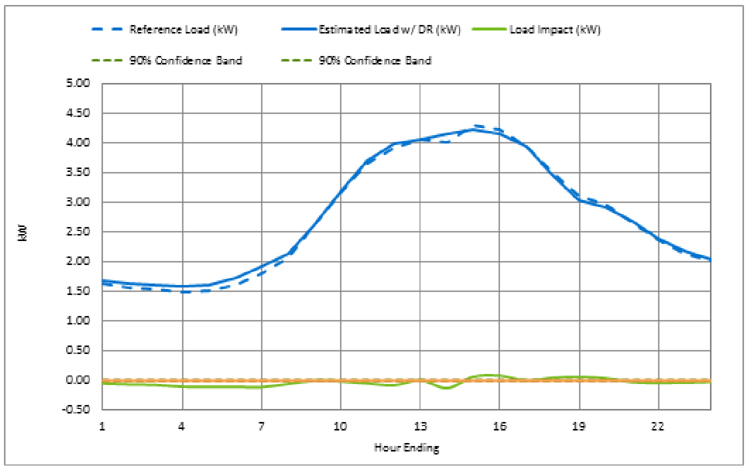
2016 Ex Post Load Impacts - Small Commercial CPP

TABLE 1: Menu options

Type of Results	Average Customer
Customer subcategory	All: All
Event Date	9/26/2016

TABLE 2: Event Day Information

Event Start	11:00 AM
Event End	6:00 PM
Total Enrolled Accounts	106,396
Avg. Load Reduction for Event Window (kW)	0.0
% Load Reduction for Event Window	**0.0%**



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	1.636	1.683	-0.048	-2.9%	70.1	-0.1	-0.1	0.0	0.0	0.0
2	1.569	1.632	-0.063	-4.0%	70.0	-0.1	-0.1	-0.1	0.0	0.0
3	1.532	1.604	-0.072	-4.7%	69.0	-0.1	-0.1	-0.1	-0.1	0.0
4	1.494	1.596	-0.102	-6.8%	68.5	-0.1	-0.1	-0.1	-0.1	-0.1
5	1.514	1.621	-0.107	-7.0%	68.9	-0.1	-0.1	-0.1	-0.1	-0.1
6	1.619	1.724	-0.105	-6.5%	70.6	-0.2	-0.1	-0.1	-0.1	-0.1
7	1.798	1.907	-0.110	-6.1%	69.6	-0.2	-0.1	-0.1	-0.1	0.0
8	2.072	2.126	-0.054	-2.6%	70.4	-0.1	-0.1	-0.1	0.0	0.0
9	2.632	2.630	0.002	0.1%	74.4	0.0	0.0	0.0	0.0	0.0
10	3.181	3.192	-0.011	-0.4%	80.2	0.0	0.0	0.0	0.0	0.0
11	3.657	3.703	-0.046	-1.2%	88.4	-0.1	-0.1	0.0	0.0	0.0
12	3.915	3.991	-0.076	-2.0%	95.2	-0.2	-0.1	-0.1	0.0	0.0
13	4.059	4.049	0.010	0.2%	97.6	-0.1	0.0	0.0	0.1	0.1
14	4.017	4.144	-0.127	-3.2%	96.0	-0.2	-0.2	-0.1	-0.1	0.0
15	4.294	4.230	0.065	1.5%	98.8	0.0	0.0	0.1	0.1	0.2
16	4.229	4.145	0.084	2.0%	99.6	0.0	0.0	0.1	0.1	0.2
17	3.944	3.946	-0.002	-0.1%	97.8	-0.1	0.0	0.0	0.0	0.1
18	3.509	3.461	0.047	1.4%	97.3	0.0	0.0	0.0	0.1	0.1
19	3.098	3.037	0.061	2.0%	94.4	0.0	0.0	0.1	0.1	0.1
20	2.962	2.925	0.037	1.3%	90.0	0.0	0.0	0.0	0.1	0.1
21	2.653	2.676	-0.024	-0.9%	85.7	-0.1	-0.1	0.0	0.0	0.1
22	2.371	2.404	-0.033	-1.4%	84.2	-0.1	-0.1	0.0	0.0	0.0
23	2.141	2.172	-0.031	-1.4%	82.5	-0.1	-0.1	0.0	0.0	0.0
24	2.024	2.040	-0.017	-0.8%	82.9	-0.1	0.0	0.0	0.0	0.0

	Reference Energy Use (kWh)	Estimated Energy Use w/ DR (kWh)	Total Load Impact (kWh)	% Daily Load Change	Cooling Degree Hours (Base 65)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily	65.9	66.6	-0.7	-1.1%	441.8	-1.1	-0.9	-0.7	-0.6	-0.4
Event	28.0	28.0	0.0	0.0%	307.0	-0.5	-0.2	0.0	0.2	0.5

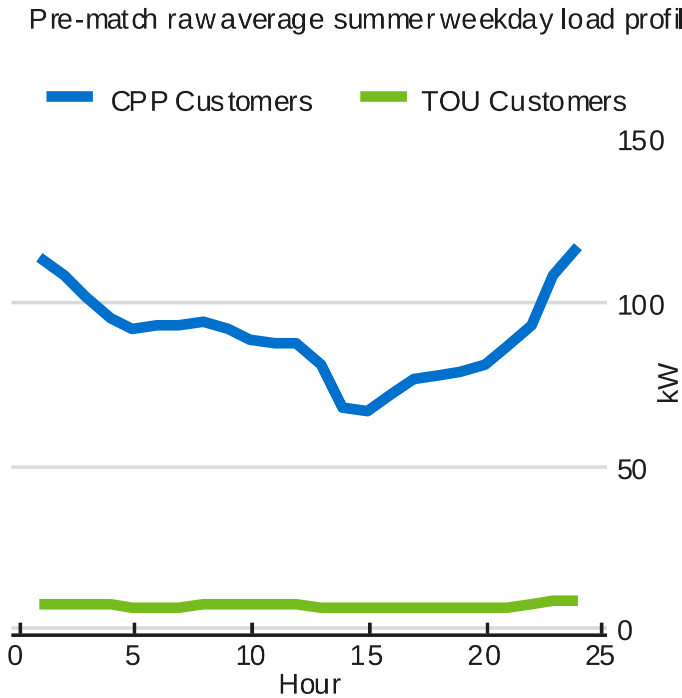
4.2 Agricultural Customer Results

Agricultural customers were exposed to a slightly different treatment than SDG&E's small commercial customers during this transition to TOU and CPP rates. Customers on PA rates were transitioned over the same period of time as the small commercial customers; however they were defaulted on to a TOU rate without a CPP component. Agricultural customers then had the option to enroll voluntarily in the CPP rate. The impact of experiencing the CPP event is expected to be slightly different for the agricultural customers due to fact that they opted in to the program. These customers are more likely to understand the rate and how to reduce load on the event days.

However, opt-in programs often have much lower levels of enrollment than default programs, where entire populations are switched on to an event based program like the small commercial CPP rate. Agricultural customers may choose to opt in based on their ability to respond, their aversion to increased event-day prices, or because they are structural winners – that is they already reduce load during normal peak hours and do not need to shift behavior to avoid penalties.

On the 2016 event day, 141 agricultural customers were enrolled in CPP out of approximately 3,800 total agricultural customers. Shown below in Figure 4-3 is the average load profile of agricultural customers on the average summer weekday. The customers that opt in to the CPP program have significantly higher average daily usage as well as a U-shaped load, with much higher consumption during the early morning and late evening than during peak hours in the middle of the day. This supports the theory that agricultural customers who opt in to CPP are structural winners; that is, they are already reducing usage in the expected time without the incentive of the rate to make them shift consumption.

Figure 4-3: Average Agricultural CPP and TOU Load Shapes

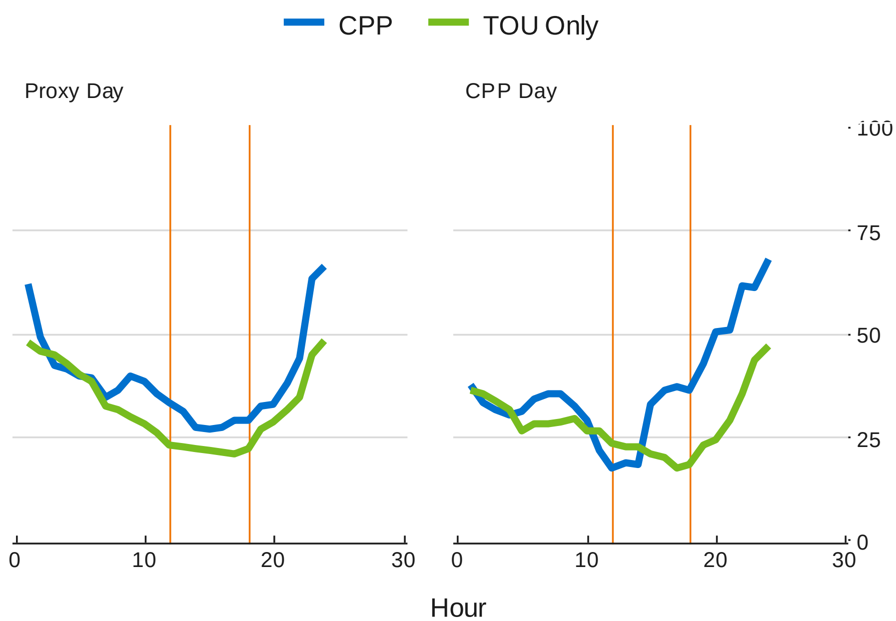


Similar to the impact analysis of the small commercial TOU customers, both a within subjects and matched control group were used to identify impacts related to the CPP event. The key challenge for the matched control analysis was to address the selection effects associated with comparing the behavior of opt-in customers with that of customers who did not opt in. Failure to address the selection effect in this case could result in biased estimates of impacts. Not only were agricultural CPP customers much larger than their TOU counterparts, they had substantially different load shapes.

As described in the methodology section, developing a matched control group is a technique used to address selection effects by attempting to pick only control group customers that are similar to the treatment customers, meaning that they behave similarly to the participants under the same conditions. Matching is accomplished by estimating a probit model using load shape and customer size to predict the likelihood that a customer would enroll in CPP. TOU customers with similar likelihoods of enrolling in the program as their CPP counterparts then form the control group. By picking only customers who are as likely to enroll in CPP but did not, the control group addresses the selection effect because the assumption is that these customers would react to the event similarly. Of course, since the TOU customer do not experience the CPP event, they can act as the counterfactual estimate of what the CPP customers could have done in the absence of the event.

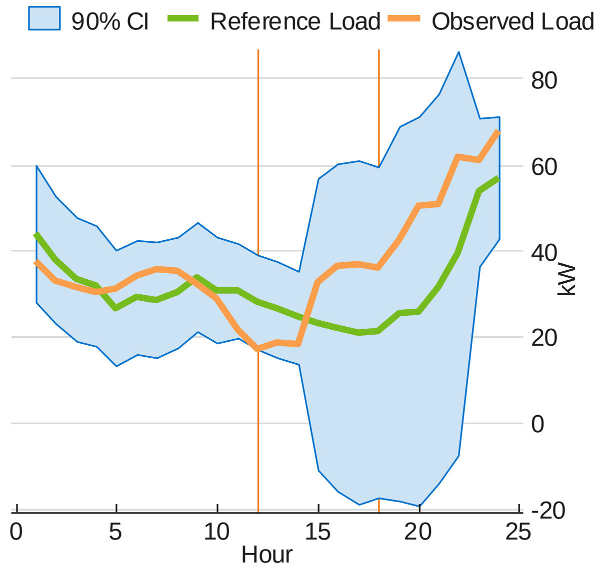
The results of the matched control group are shown below in Figure 4-4. The customers were matched to each other on summer non-event day load shapes, however due to the size difference between large CPP customers and their TOU counterparts, a suitable match was not found for the extremely large CPP customers. This further reduced the size of the CPP participant pool to roughly 90 customers who were successfully matched. The graph on the left of the figure shows the average load shape on five non-event proxy days. Overall, the load profiles of the matched TOU customers look quite similar to that of the TOU customers in both magnitude and load shape. The event day average customer load shapes are shown on the right, with the event hours bracketed using vertical lines. In general, there is not much evidence that these matched CPP customers responded to the event except in the first hour.

Figure 4-4: Matched Control Group on Proxy Event Days and the Event Day



However, to understand the extent to which the results shown above are significant, a difference in differences regression specification was run on the matched control data. The specification is the same as the one used for the small commercial impacts. The results are shown in Figure 4-5. The light blue band around the reference load indicates the degree of variability around the reference load based on a 90% confidence interval. As the observed load stays within the confidence interval of the reference load, they cannot be distinguished with any statistical significance. This in turn, implies that the impacts themselves are not statistically significantly different from 0.

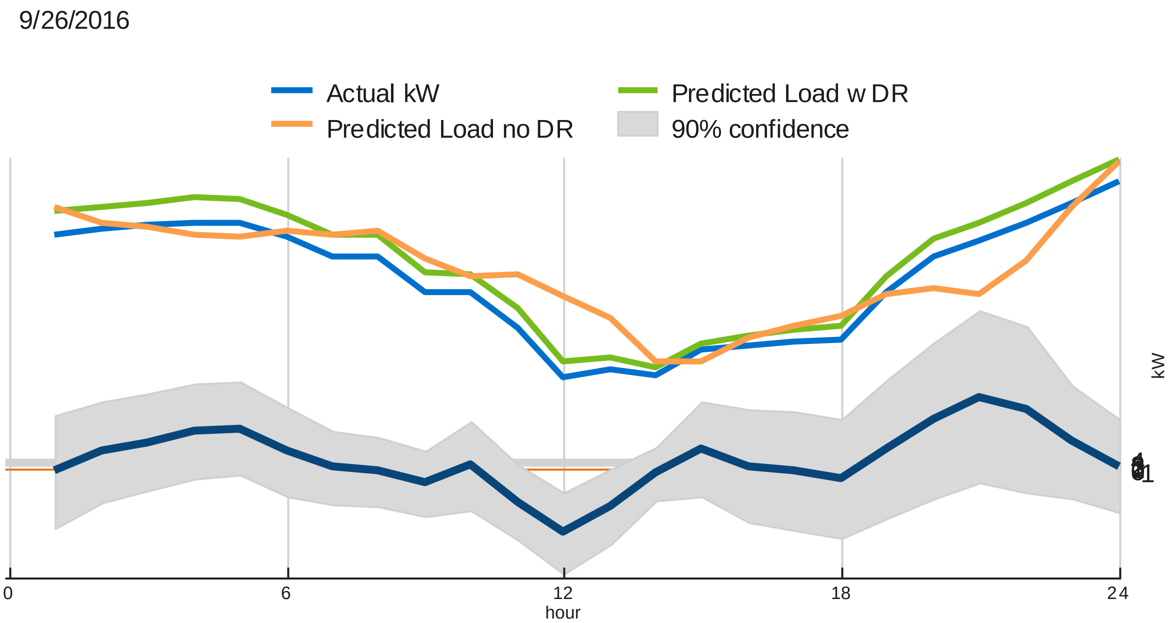
Figure 4-5: Difference in Differences Agricultural Customer Impacts



To address the challenges of matching the agricultural CPP customers to their TOU counterparts, Nexant additionally estimated the results of the CPP impacts using a within subjects method, where non-event days were fit to a regression model and used to predict the reference load, or counterfactual, on the event day. Because no matching is needed for this method, the data from the full 141 customers could be used.

The model used to predict the load on the event day was based on model 5; the same specification as was used for the small commercial customers. However, an additional variable was added to explain the more extreme seasonality in load experienced by the agricultural customers. In addition to weather, month, and day of week variables, a lagged dependent variable was added. This value corresponds to the average hourly impact in the week prior to the day and hour being estimated – essentially capturing the fact that agricultural loads are driven by weather and planting, watering, and harvesting schedules that a small commercial customer would not be affected by. The results of this analysis are shown in Figure 4-6. Similar to the results from the matched control group, there appear to be some indication that customers are responding during the first hour of the event, but the small sample size and high variability in the agricultural customer loads prevent any further conclusions from being drawn, as the confidence interval around the impact estimate for the remaining event hours includes zero.

Figure 4-6: Within Subjects Agricultural Customer CPP Impacts



5 TOU Ex Post Load Impact Estimates

5.1 Small Commercial TOU Results

The results of the true transition as well as ten different false experiments are shown in Figure 5-1. Ten false transition dates were chosen from the summer of 2015. Note that customers who had already opted in to the TOU rate were excluded from these results as they had transitioned by the time of the false experiments. These results demonstrate both the range of variability in the underlying data as well as the true results for the TOU transition; with a range of impacts +/-10% from a mean of roughly 0. This corresponds to impacts in the +/-0.2 to 0.4kW range. False experiment results ranged in confidence bands between +/- 5% for weekday results and +/-10% for weekend results. This implies that any impacts associated with the TOU transition that resulted in load impacts smaller than 5-10% would not be able to be detected.

The only significant impacts were a reduction in the demand associated with weekday off peak usage and a slight increase in weekday part-peak usage. This indicates that customers were using less energy during weekday evenings, when energy prices are at their lowest, and using more during the 6-11am and 6-10pm. Contrary to the expected economic theory, which suggests that customers would shift usage from peak and part-peak periods to relatively lower-cost periods such as off-peak periods resulting in increased use, customers did the opposite. Multiple false experiment results showed significant increases or decreases, however, which indicates that the model cannot distinguish treatment effects from noise, resulting in false precision. So while some significant impacts were found for the customers on the TOU-CPP rate, these should not necessarily be interpreted as true effects of the TOU rate.

Figure 5-1 summarizes the impacts due to SDG&E's implementation of mandatory TOU rates for each rate period. It presents the average reduction by season, day type and rate period for small commercial customers. With DR, however, the reductions attained during peaking conditions rather than on the average weekday are often of more interest.

Rate blocks were split according to summer and winter seasons, weekday or weekend day type, and the time-varying rate category: on peak, semi-peak (or shoulder peak time), and off peak. Table 5-1 gives the schedule of rate categories for each season. Note that holidays follow a weekend schedule, regardless of season.

Table 5-1: TOU Rate Schedule

Season	Day Type	Rate Block	Time
Winter	Weekend	Off Peak	All Day
	Weekday	Off Peak	10pm-6am
		Semi Peak	6am-5pm 8pm-10pm
		On Peak	5pm-8pm

Summer	Weekend	Off Peak	All Day
	Weekday	Off Peak	10pm-6am
		Semi Peak	6am-11am 6pm-10pm
		On Peak	11am-6pm

The results of the true transition as well as ten different false experiments are shown in Figure 5-1. Ten false transition dates were chosen from the summer of 2015. Note that customers who had already opted in to the TOU rate were excluded from these results as they had transitioned by the time of the false experiments. These results demonstrate both the range of variability in the underlying data as well as the true results for the TOU transition; with a range of impacts +/-10% from a mean of roughly 0. This corresponds to impacts in the +/-0.2 to 0.4kW range. False experiment results ranged in confidence bands between +/- 5% for weekday results and +/-10% for weekend results. This implies that any impacts associated with the TOU transition that resulted in load impacts smaller than 5-10% would not be able to be detected.

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Figure 5-1: Summer TOU Impacts by Weekday and Rate Block

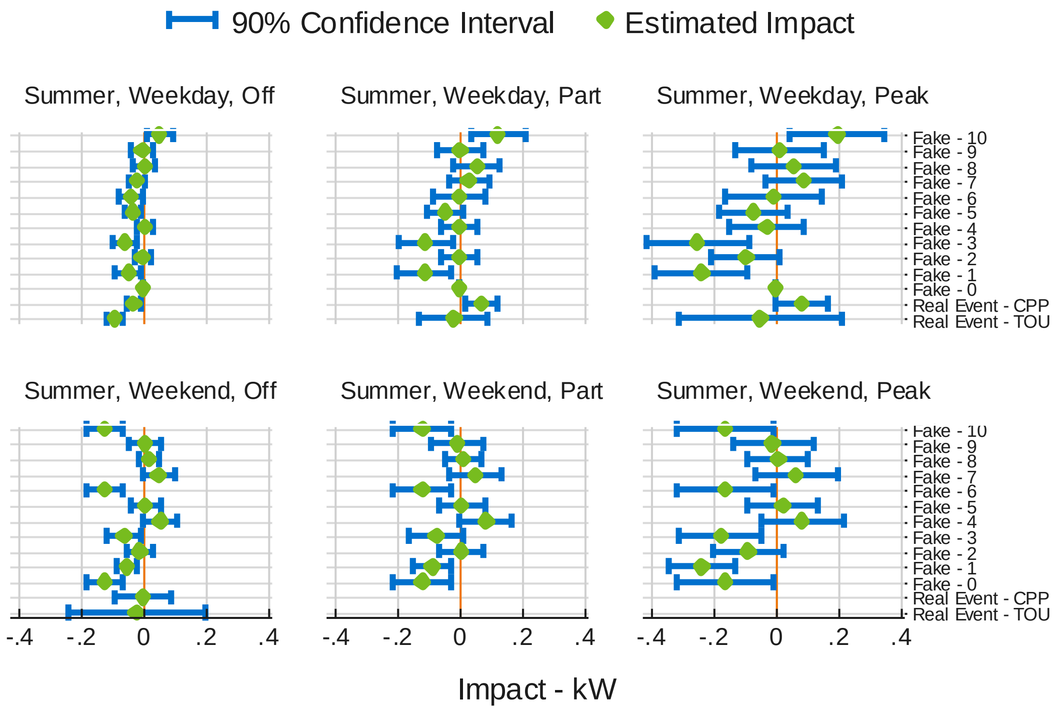

Figure 5-2: Hourly Summer TOU Impacts

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2016 Ex Post Load Impacts - TOU Impacts

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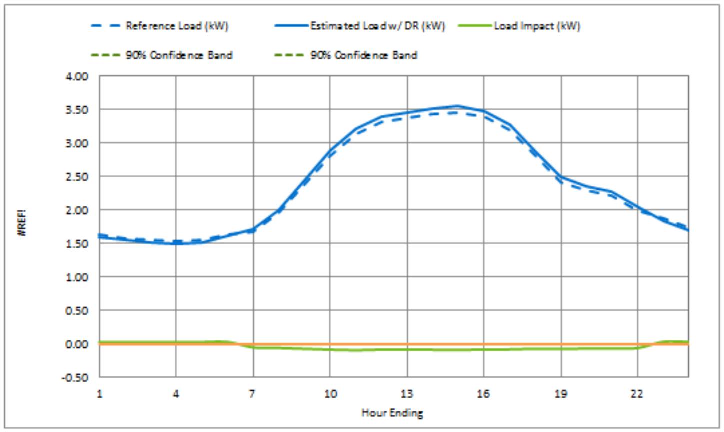
TABLE 2: Event Day Information

Type of Results	Average Customer
TOU Rate	All TOU
Customer Category	All: All
Day Type	Weekday
Season	Summer

TABLE 2: Typical Day Information

Event Start	All Day
Event End	All Day
Total Enrolled Accounts	118,160
Avg. Load Reduction for Peak Hours (kW)	-0.1
% Load Reduction for Peak Hours	-2.4%



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	%Load Reduction	Temperature (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	1.6	1.6	0.0	2.0%	65.5	0.016	0.026	0.033	0.040	0.050
2	1.6	1.6	0.0	2.0%	65.1	0.016	0.025	0.032	0.039	0.048
3	1.6	1.5	0.0	2.0%	64.8	0.015	0.025	0.031	0.038	0.047
4	1.5	1.5	0.0	2.0%	64.6	0.015	0.025	0.031	0.037	0.047
5	1.6	1.5	0.0	2.0%	64.4	0.015	0.025	0.031	0.038	0.047
6	1.6	1.6	0.0	2.0%	64.1	0.016	0.026	0.033	0.040	0.050
7	1.7	1.7	0.0	-2.9%	64.0	-0.077	-0.060	-0.048	-0.036	-0.019
8	1.9	2.0	-0.1	-2.9%	64.6	-0.090	-0.070	-0.056	-0.042	-0.022
9	2.4	2.5	-0.1	-2.9%	66.5	-0.110	-0.085	-0.068	-0.051	-0.027
10	2.8	2.9	-0.1	-2.8%	69.1	-0.130	-0.101	-0.080	-0.060	-0.031
11	3.1	3.2	-0.1	-2.8%	71.8	-0.144	-0.112	-0.089	-0.067	-0.035
12	3.3	3.4	-0.1	-2.4%	74.0	-0.153	-0.110	-0.079	-0.049	-0.006
13	3.4	3.5	-0.1	-2.4%	75.6	-0.156	-0.112	-0.081	-0.050	-0.006
14	3.4	3.5	-0.1	-2.4%	76.4	-0.159	-0.113	-0.082	-0.051	-0.006
15	3.5	3.5	-0.1	-2.4%	76.6	-0.160	-0.114	-0.083	-0.051	-0.006
16	3.4	3.5	-0.1	-2.4%	76.3	-0.156	-0.112	-0.081	-0.050	-0.006
17	3.2	3.3	-0.1	-2.4%	75.5	-0.147	-0.106	-0.077	-0.048	-0.006
18	2.8	2.9	-0.1	-2.4%	74.4	-0.130	-0.093	-0.068	-0.042	-0.006
19	2.4	2.5	-0.1	-2.9%	72.8	-0.112	-0.087	-0.070	-0.052	-0.028
20	2.3	2.4	-0.1	-2.9%	70.5	-0.106	-0.082	-0.066	-0.050	-0.026
21	2.2	2.3	-0.1	-2.9%	68.2	-0.102	-0.080	-0.064	-0.048	-0.026
22	2.0	2.1	-0.1	-2.9%	67.0	-0.092	-0.072	-0.058	-0.043	-0.023
23	1.9	1.8	0.0	2.0%	66.2	0.019	0.030	0.038	0.045	0.057
24	1.7	1.7	0.0	2.0%	65.7	0.017	0.028	0.035	0.042	0.052
	Reference Energy Use (kWh)	Estimated Energy Use w/ DR (kWh)	Total Load Impact (kWh)	% Daily Load Change	Average Temperature	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily (kWh)	57.1	57.9	-0.9	-1.6%	69.3	-1.1	-1.0	-0.9	-0.8	-0.7

5.2 Agricultural Customer TOU Results

Approximately 3,800 agricultural customers were defaulted on to a TOU rate during period of November 2015 through April 2016. Similar to the small commercial customers, no control group was able to be withheld from the rate transition. As a result of this, there were no agricultural customers remaining on a flat rate to form a basis of comparison during the post-transition summer. This in turn makes assigning any causal relationship between the implementation of TOU rates and subsequent rate changes extremely challenging.

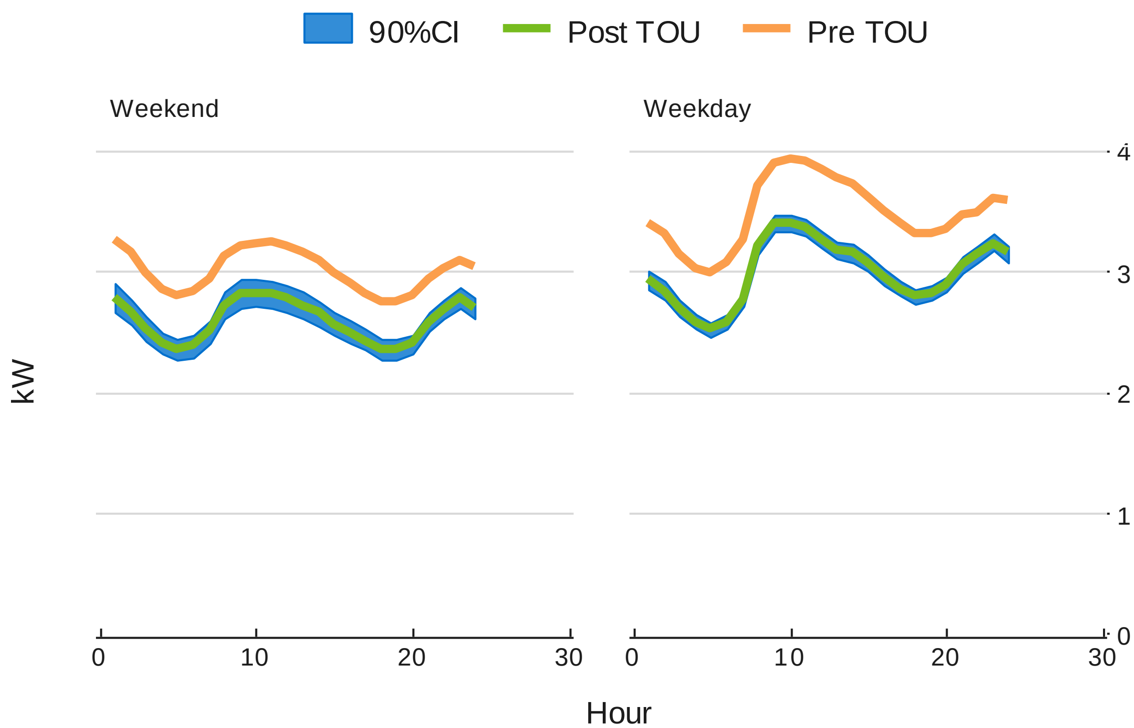
To assess the degree to which agricultural customers began to shift their load in response to TOU price signals, Nexant first assessed the change in daily load consumption per rate block. The rate blocks for agricultural customers are the same as those for the small commercial customers, summarized in Table 5-1. If load shifting is occurring, the percentage of daily consumption in each rate block would change from the pre-transition period to the post-transition period. Table 5-2 shows the result of this analysis. Consumption across periods did not shift substantially; off peak consumption stayed the same, and a slight increase in semi-peak consumption during weekdays was offset by a slight decrease in weekday on-peak consumption. These shifts, however, are too small to be distinguishable from noise.

Table 5-2: Agricultural Customer Consumption Shares by Summer Rate Block

Weekday	Rate Block	Avg kW Pre	Avg kW Post	Share Pre	Share Post
Weekend	Off Peak	3.0	2.6	100.0%	100.0%
Weekday	Off Peak	3.3	2.8	31.3%	31.3%
	Semi Peak	3.6	3.1	34.3%	34.8%
	On Peak	3.6	3.1	34.4%	33.9%

Looking at the average weekday load profile in the pre and post-transition period shown in Figure 5-3, no visual evidence of load shifting appears. However, the overall daily consumption used is significantly lower in the post-TOU summer data. While this result is statistically significant, it cannot be causally attributed to the introduction of TOU rates. As discussed above, the lack of control group prevents the evaluator from being able to assign causality of the TOU implementation to the resulting energy conservation. Other factors, especially the impacts of drought conditions, could have had an impact for these highly weather-sensitive customers. Again, while customers may have in fact responded to the TOU rates, the experimental design and lack of a control group limits the ability to detect these impacts or to say definitively that they are statistically distinguishable from zero.

Figure 5-3: Hourly Summer Load Profiles for Agricultural Customers



6 Ex Ante Methodology

Because the evaluation did not produce any significant ex post impacts for either the CPP or TOU components of the small commercial or agricultural rate transition, ex ante impacts were not estimated. As discussed above, while there are some customer segments that produced significant impacts, no significant impacts were observed overall. It is important to note that with a confidence interval of 95%, roughly one significance test in 20 will pass, regardless of whether or not a true relationship exists between the treatment and the outcome.

For all TOU and CPP rates there are five main steps to producing ex ante impacts:

1. Analyze how enrollment varies across customer segments and ensure the starting load values reflect those segments. This step is particularly important for opt-in and default options because customers who enroll and remain on time varying rates self-select and likely differ from the average customer.
2. Run regression models based on actual electricity use patterns of the participant group under flat rates and use those models to estimate reference loads under 1-in-10 and 1-in-2 weather conditions.
3. Calculate the impact estimates obtained from the ex post analysis to the reference loads to get percent impact reductions. The percent reduction for each segment is applied to the reference load to get a per-customer kW reduction.
4. Calculate per customer load reductions by applying the percent load reductions to customer 1-in-2 and 1-in-10 reference loads.
5. Combine per customer impacts for each of the relevant customer segments with forecasted enrollment levels. It is important to ensure the load reflects the type of customers who enroll and remain on time-varying rates.

7 Conclusions and Recommendations

Overall, no significant impacts were observed from the transition of SDG&E's small commercial customer population to TOU and TOU-CPP rates. Challenges relating to implementation, notification and experimental design hampered efforts to identify impacts from the transition. As a result, no ex ante results are estimated as ex post impacts could not be distinguished from zero. However, while these challenges ultimately meant that no impacts could be distinguished, that does not imply that the impacts are in fact zero.

Future evaluations may be able to identify impacts from the large group of small commercial and agricultural customers enrolled in CPP programs. As more events are called, customers will be able to observe the impact of event based pricing on their bills, and learn to modify behavior when called on to respond. In this way, CPP impacts may develop over time. Improvements to the event notification process may also facilitate this development, as customers can only respond to events they know are occurring. By testing communication systems and reaching more customers prior to an event, either through encouraging customers to sign up for notification or automatically notifying customers through email, phone, or SMS, SDG&E may improve the response rate of customers on CPP events.

By calling more events, SDG&E may ultimately have more data points from which to draw conclusions about the small commercial customer's ability to respond to CPP events. Attention should also be paid to the type of days on which an event is called. The 2016 evaluation was hampered by the extreme late-season day on which ex post estimates were calculated. More summer events, scheduled during the week when commercial customers may best be able to respond, may provide better information about this population.

All customers on TOU rates can learn over time to shift their consumption to reflect the prices they experience. Without a control group, however, little information about these changes will be able to be attributed to the effects of TOU. Therefore, for future large-scale default rate transitions, proper planning must include planning for impact evaluation. Of particular note is the upcoming transition of all of SDG&E's residential customers to default TOU rates. Without withholding representative control groups in these customer classes, any changes in customer behavior will be similarly difficult, if not impossible, to identify.