REPORT

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2019 SCE Real Time Pricing Demand Response Evaluation

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Prepared for Southern California Edison

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Confidential information is redacted and is denoted with black highlighting: [redacted]

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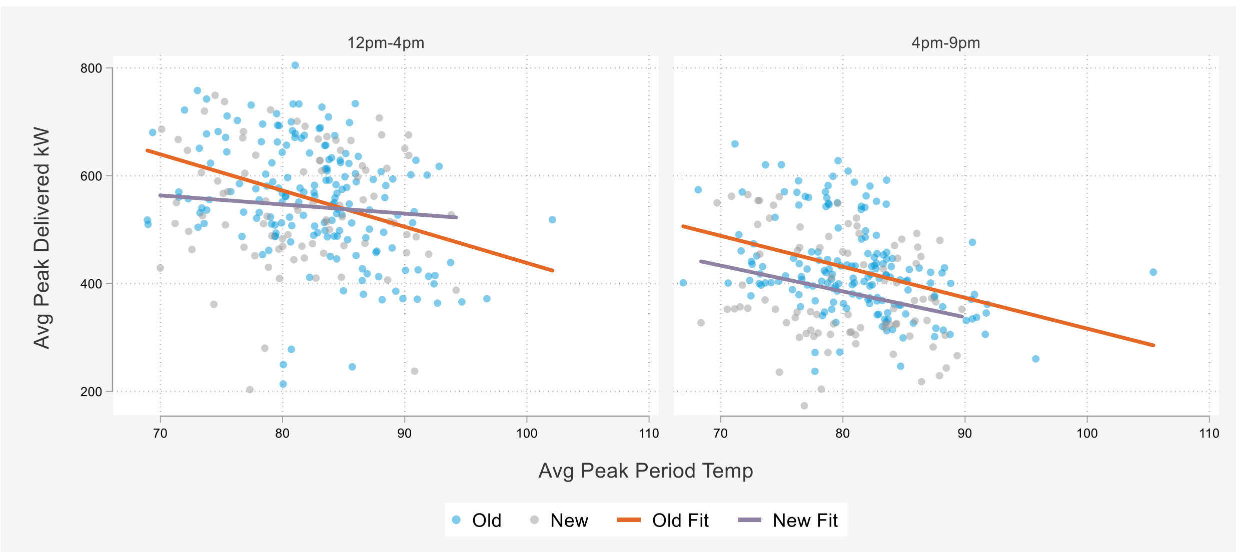
1 EXECUTIVE SUMMARY

The Real-Time Pricing Program offers commercial and industrial customers the opportunity to react daily to price signals and reduce loads when prices are high. Each day, the next days' hourly prices are tied directly to the daily maximum temperature in Downtown Los Angeles, grouped in to one of seven day types: Hot Summer Weekday, Moderate Summer Weekday, Mild Summer Weekday, High Cost Winter Weekday, Low Cost Winter Weekday, High Cost Weekend and Low Cost Weekend.

There are currently approximately 100 customers enrolled in the RTP program. In the summer of 2019, the RTP tariff moved from nine different day types to seven and shifted the peak windows and price ratios associated with each price. This has important implications for the evaluation. In addition to capturing the ex post and estimating ex ante program impacts, a key question for this year's evaluation is how customers responded to the new rate structure. In short, there is clear evidence of customer response to the new rate, which is summarized in Figure 1.

Figure 1: Peak Period Rate Shifting



Several insights can be gleaned from this figure.

- Customers in 2019 reduced their consumption in the 4pm-9pm window compared to 2018.
- Regardless of RTP day type classification and its changes, customers exhibited the same downward trend in consumption in 4pm-9pm across both summers.
- Customers in 2018 had the same relationship between hotter days and lower loads during the 12pm-4pm window as during the 4pm-9pm window.
- Customers in 2019 did not have a statistically significant negative relationship between hotter days and lower consumption in the 12pm-4pm window.

This is clear evidence that customers respond to the new price signals, regardless of modeling choices made.

RTP enrollments are expected to decline over time, from 102 in 2020 to 70 enrolled customers in 2030. Once the RTP program reaches a steady state in 2024 with constant, aggregate August Peak Day impacts will be 15.0MW. Per the ex post modeling, no weather variables are included in the ex ante specification, so the only difference between these scenarios is the RTP day type associated with the CAISO and SCE 1-in-2 and 1-in-10 weather scenarios. All August Monthly Peak days are associated with the 'Hot Summer Weekday' RTP day type and have the same rate schedule applied. Finally, the decrease in impacts over time is attributable to a decline in program enrollment over the forecast horizon.

Table 1: RTP Aggregate Program Ex Ante Impacts - August Peak Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2020	21.86	21.86	21.86	21.86
2021	20.15	20.15	20.15	20.15
2022	18.43	18.43	18.43	18.43
2023	16.72	16.72	16.72	16.72
2024	15.00	15.00	15.00	15.00
2025	15.00	15.00	15.00	15.00
2026	15.00	15.00	15.00	15.00
2027	15.00	15.00	15.00	15.00
2028	15.00	15.00	15.00	15.00
2029	15.00	15.00	15.00	15.00
2030	15.00	15.00	15.00	15.00

The RTP program experienced many major changes in 2019 that make comparison to prior years difficult. These changes included

- Substantial customer churn in the fall of 2018 and spring of 2019
- Change in ex ante weather conditions
- New TOU rate blocks for both RTP and otherwise applicable tariffs
- Narrower peak period RTP pricing
- Consolidation of RTP summer weekday day types from five to three

As a result, considerable changes to the ex post and ex ante results were not unexpected. Nevertheless, the program continues to deliver peak period reductions of approximately 30% on Hot Summer Weekdays. Factoring in customer churn, updated consumption patterns, and updated rates for ex ante forecasts, customers can experience nearly 47% impacts during the RA window on Hot Summer Days going forward.

Of considerable interest for subsequent years will be customer response over time as customers become acquainted with the new price schedules. Since the new rates went in to effect between March 1 2019 and June 1 2019, they have only experienced between five and six months of the new tariffs as of this evaluation. With more time on the new rates, their response patterns may change and reflect their ability to reduce loads in the 4pm-9pm window more consistently.

2 PROGRAM DESCRIPTION

The Real Time Pricing (RTP) program is a variable tariff-based demand response program for commercial and industrial customers in SCE's territory. The basis of the tariff is hour-specific generation energy prices that are set based on the daily maximum temperature in Downtown Los Angeles on the prior day. Seven potential day types are available, including three summer weekday schedules, high and low cost winter weekdays, and high and low cost weekends. The rate is available to commercial, industrial, and agricultural customers on rates TOU-8, TOU-8 Standby, TOU-GS1, TOU-GS2, TOU-GS3, TOU-PA2 and TOU-PA3. Customers may be dually enrolled in the Agricultural and Pumping Interruptible Program or Base Interruptible Program.

Both RTP and other commercial and industrial rates underwent a change starting in March 2019, where the peak period changed from 1pm – 6pm to 4pm – 9pm. RTP rates also consolidated their day type structures; from nine separate price schedules to seven. A more detailed exploration of these rate changes are explored in the subsequent sections.

There were approximately 102 customers enrolled on RTP rates as of the PY 2019 summer season, down from 128 in last year's evaluation. As this program is rate-based, customer counts tend to fluctuate over time.

2.1 KEY RESEARCH QUESTIONS

The PY2019 evaluation of SCE's RTP program sought to answer these key research questions:

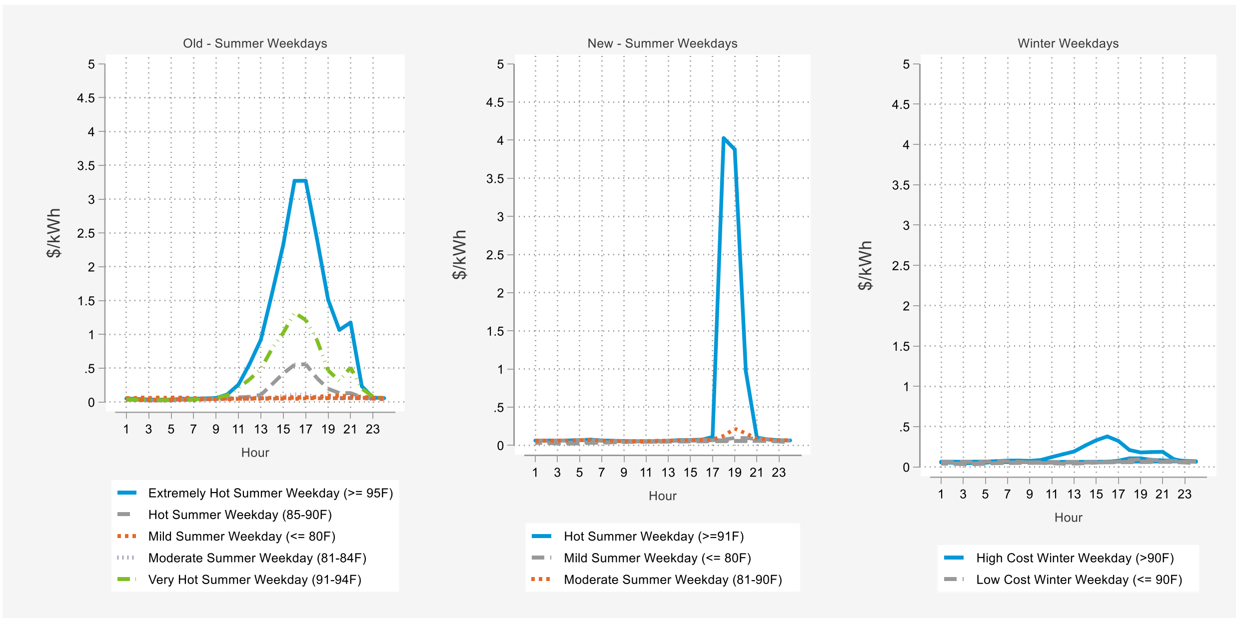
- What were the demand reductions due to program operations and interventions in 2019 – for each RTP day type, monthly average weekday and monthly peak day? How do these results compare to the ex post results from the prior year and why?
- What was the impact of the March 2019 RTP rate change on customer consumption patterns?
- How do load impacts differ for customers who have enabling technology and/or are dually enrolled in other programs?
- How do weather and event conditions influence the magnitude of demand response?
- How do load impacts vary for different customer sizes, locations, and customer segments?
- What is the ex ante load reduction capability for 1-in-2 and 1-in-10 weather conditions? And how well do these reductions align with ex post results and prior ex ante forecasts?
- What concrete steps can be undertaken to improve program performance?

2.2 PROGRAM DESCRIPTION

The Real Time Pricing Program offers commercial and industrial customers the opportunity to react daily to price signals and reduce loads when prices are high. Each day, the next days' hourly prices are tied directly to the daily maximum temperature in Downtown Los Angeles, grouped in to one of seven day types: Hot Summer Weekday, Moderate Summer Weekday, Mild Summer Weekday, High Cost Winter Weekday, Low Cost Winter Weekday, High Cost Weekend and Low Cost Weekend.

There are currently approximately 100 customers enrolled in the RTP program. For the summer of 2019, the RTP tariff moved from nine different day types to seven and shifted the peak windows and price ratios associated with each price. This has important implications for the evaluation. In addition to capturing the ex post and estimating ex ante program impacts, a key question for this year's evaluation will be how customers responded to the new rate structure.

Figure 2: Changes in Real Time Pricing Tariff Structure

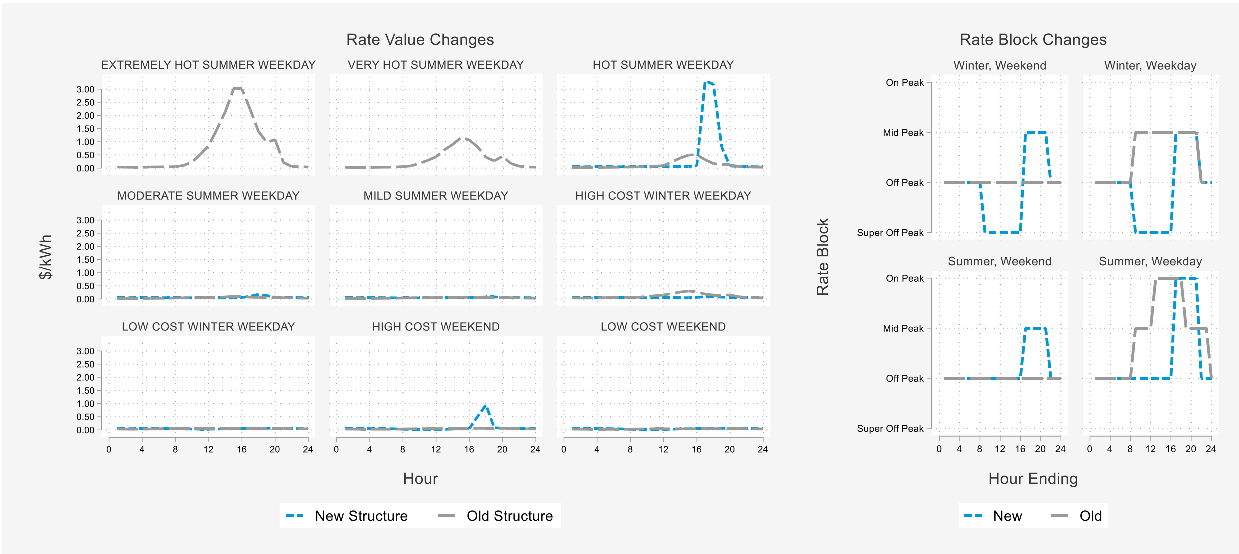


As shown in Figure 2, the change in RTP tariff in March of 2019 altered the rate that participants would experience, especially on summer weekdays. There are three main effects of the rate change:

1. The price ratio of peak to off-peak has increased substantially for the hottest summer days. The peak price per kWh is now over $4.00, compared to approximately $3.25 for extremely hot days and $1.32 for very hot days in the prior regime.
2. The peak hours have narrowed to reflect CAISO's new peak, from 4 pm to 9 pm, compared to a broader all-afternoon peak earlier.
3. The number of RTP day types has been condensed, from 5 to 3 summer weekday day types (weekends and winter weekdays were unchanged).

These rate changes were accompanied, to an extent, with rate changes in RTP participants' otherwise-applicable tariff (OAT). The OAT is the rate under which a participant would be billed if they had not been enrolled in RTP. It is essentially the counterfactual rate and its price structure is used to predict participants' reference loads to determine program impacts. **Figure 3** summarizes the differences in both the RTP generation prices to which customers are exposed and the change in peak period definitions. The peak period definition shift is critical for correct modeling of both ex post and ex ante rates, as these are periods when both delivery and generation demand charges apply.

Figure 3: Old and New Rate Blocks and RTP Rates



The changes in rate blocks compared to prior years can be summarized as follows:

- ‘On peak’ definition is shifted later in the day; from 4pm-9pm compared to 1pm-6pm previously
- Transition to ‘on peak’ hours does not pass through an intermediate ‘mid peak’ period as in prior years
- Weekends now have variable rate blocks and are no longer classified as ‘off peak’ for 24 hours
- An additional rate block – ‘super off peak’ – is introduced on winter days.

Strictly on the basis of these rate changes, we should expect substantial differences in ex post impacts compared to last year.

2.3 PARTICIPANT CHARACTERISTICS

There were 102 commercial, industrial, and agricultural customers active on RTP as of the 2019 peak day, September 4th. Table 2 summarizes their key characteristics. “Manufacturing” was the most common customer industry, with “Wholesale, Transport, Other Utilities and Agriculture, Mining and Construction” following. The majority of customers are on the industrial TOU-8 rate. A small subset of customers has onsite solar generation, but equally, a number of customers are on a standby rate – either TOU-8-S or TOU-GS1-S. While “NEM- Solar” customers tended to have some level of export during mid-day hours, some of the standby customers also have significant electricity exports.

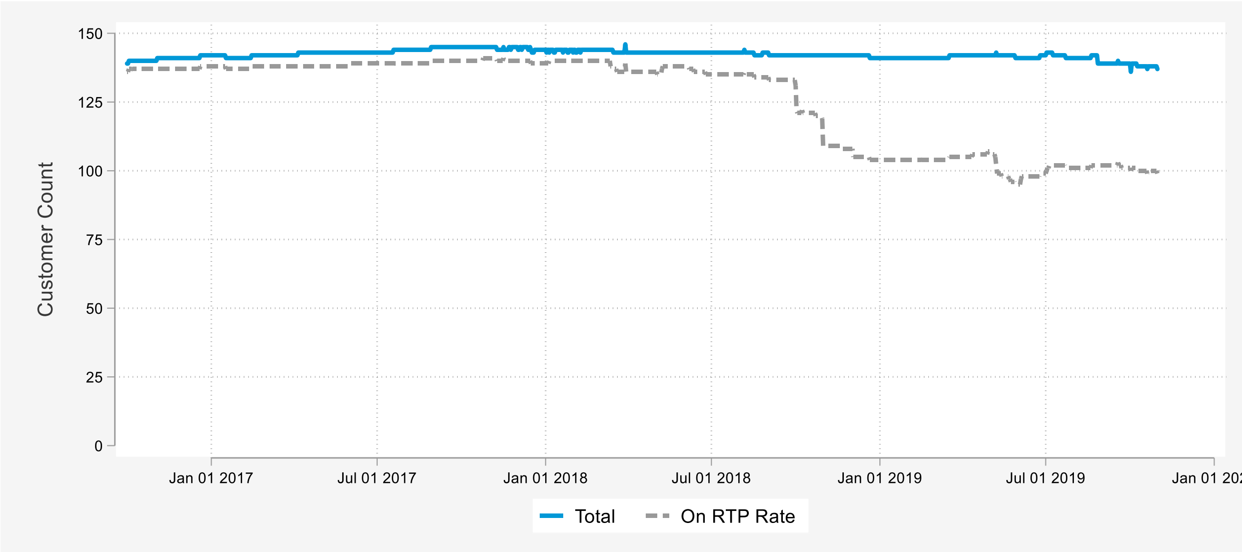
Table 2: Participant Characteristics on 9/4/2019 Peak Day

Category	SubCategory	Customer Count
Rate Family	TOU-8	58
	TOU-GS1	15
	TOU-GS3	8

Category	SubCategory	Customer Count
	TOU-GS2	8
	TOU-PA-2	7
	TOU-8-S	4
	TOU-PA-3	2
Industry	Manufacturing	35
	Wholesale, Transport, Other Utilities	21
	Agriculture, Mining, Construction	19
	Offices, Hotels, Finance, Services	17
	Institutional/Government	4
	Unknown/Other	4
	Retail Stores	1
	Schools	1
LCA	La Basin	78
	Big Creek/Ventura	17
	Non-Lca	7
NEM Type	None	100
	Solar	2
Size	Greater Than 200kW	73
	20kW Or Lower	16
	20-200kW	13
Weather Station	173	30
	121	17
	193	8
	122	7
	171	7
	112	7
	172	5
	113	4
	194	3
	111	3
	132	3
	161	2
	181	1
	151	1
	191	1
	101	1
	51	1
	141	1
Zone	Remainder Of System	66
	South Of Lugo	23
	South Orange County	13

Enrollment in RTP was steady until approximately October of 2018, when nearly 30 accounts left the program, as shown in Figure 4. The drop in enrollment is attributable to customers opting out of the RTP program after a summer of many hot days and consequently high bills.

Figure 4: RTP Enrollment over Time



2.4 2019 EVENT CONDITIONS

RTP events are called based on temperature conditions on the prior day in Downtown Los Angeles; essentially every day experiences a treatment, though the treatments themselves vary. In March of 2019, the RTP day types were updated in conjunction with the larger rate changes discussed earlier. In effect, both the number and criteria for the event days changed – most dramatically for summer weekdays. What used to be broken down in to five distinct summer weekday options (Extremely Hot, Very Hot, Hot, Moderately Hot, and Mild) was now consolidated to only three day types (Hot, Moderately Hot, and Mild). The temperature ranges for these dispatch types also changed in this period, for example, the Moderate Summer Weekday used to be assigned for temperatures between 81F-84F whereas it is now called between 81F and 90F. A full breakdown of these temperature changes is shown in Table 3.

Table 3: Old and New Event Dispatch Criteria

Day Type	Old Dispatch Criteria	New Dispatch Criteria	Difference
Extremely Hot Summer Weekday	≥95		Eliminated
Very Hot Summer Weekday	91-94		Eliminated
Hot Summer Weekday	85-90	> 91	No Overlap
Moderate Summer Weekday	81-84	81-90	Some Overlap
Mild Summer Weekday	≤80	≤80	Same
High Cost Winter Weekday	>90	>90	Same
Low Cost Winter Weekday	≤90	≤90	Same
High Cost Weekend	≥78	≥78	Same
Low Cost Weekend	<78	<78	Same

This reassignment of RTP day types has important implications for the PY2019 analysis. Two day types no longer exist, one has different dispatch criteria despite being called the same thing, and another has only some overlap in the dispatch criteria. This means that any comparison of summer weekdays between this summer and last summer will need to be carefully considered.

Another consideration when comparing impacts between this year and prior years will be the *distribution* of days of each day type. Because of the changing event definitions, having five "Hot Summer Weekdays" in 2018 is not the same as having five "Hot Summer Weekdays" in 2019. A comparison of the number of days of each time is shown in Table 4. The first series of columns show the definitions of event days as they were defined when they occurred. That is, days before March 1, 2019 used the old day type definition and the days after used the new. However, the second series of columns (to the right) show what the distribution of event days would be if consistent definitions were used. Using the new definitions, for example, there were only 9 days with temperatures above 91F in the summer of 2019. Using the old definition, however, there were 24. The difference is attributable to the difference in temperature definition – above 91F in the new scenario or between 85F-90F in the old scenario.

Table 4: Distribution of Event Types by Method

	Using Contemporary Definitions			Using Consistent (Old) Definitions		
Day Type	PY2017	PY2018	PY2019	PY2017	PY2018	PY2019
Extremely Hot Summer Weekday	3	6		3	6	7
Very Hot Summer Weekday	8	4		8	4	8
Hot Summer Weekday	22	25	10	22	25	23
Moderate Summer Weekday	25	18	43	25	18	15
Mild Summer Weekday	23	28	27	23	28	27
High Cost Winter Weekday	9	2	5	9	2	5
Low Cost Winter Weekday	161	168	165	161	168	165
High Cost Weekend	25	20	15	25	20	15
Low Cost Weekend	47	52	58	47	52	58

2.5 PROGRAM CHARACTERISTICS THAT INFLUENCE EVALUATION

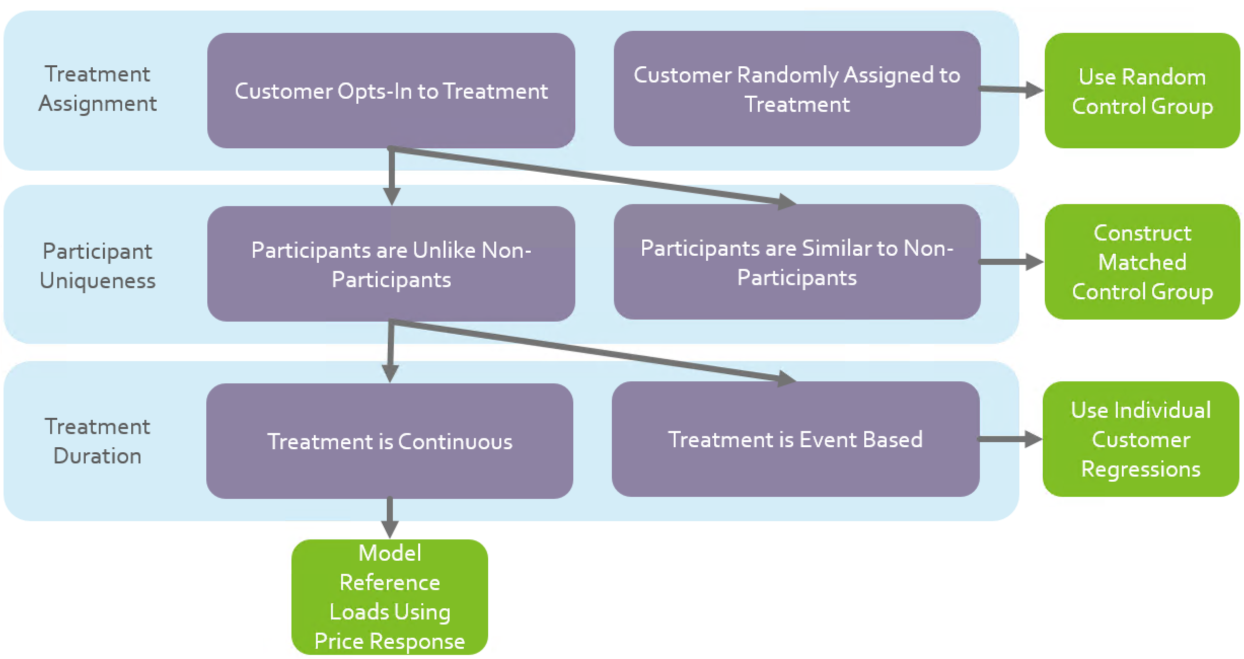
A substantial challenge for the evaluation of rate-based demand response, especially when the program is one that a customer can opt in to, is the difficulty of finding a valid counterfactual. The counterfactual load for a customer enrolled in RTP is what the customer would consume if they were billed on their otherwise applicable tariff. Because we cannot observe customers on the OAT, we must estimate it. The characteristics of the RTP participants and program design make this challenging and should be carefully considered as part of the evaluation planning process. The three characteristics that most affect the evaluation choice are:

- **Treatment assignment:** RTP customers opt into the program.

- **Uniqueness:** Participants are large and have unique loads and processes that make finding comparable customers difficult.
- **Treatment duration:** Once on the rate, customers remain on it. There is no event day comparable to BIP or API.

A summary of the implications of these characteristics is shown in **Figure 5**. When customers can be randomly assigned a rate, such as when a default Time-of-Use rate is rolled out in staggered waves, there are customers who experience the OAT and who can function as a control. For the RTP program, however, customers opt into the program. Customers who opt in tend to be different than customers who do not; they may have more flexibility in their loads, they may be larger or smaller, or they may be more likely to be a standby customer or in a particular industry or location. In some cases, a matched control group could be constructed to find a statistically similar population of customers to participants, however that approach requires that a similar group of non-participants exist in the population. For programs like RTP, where there are large, unique customers, this is unlikely to be the case. What remains, then, is to use participant consumption data to model the counterfactual. This approach requires a sufficient amount of unperturbed data from which to fit the model. This can be easy, as in the evaluation of the Agricultural Pumping Interruptible program, where events occur one or two days out of the year and the remaining days are unperturbed. When a demand response program operates continuously, as with RTP, pre-treatment data is likely to reflect an outdated model of how a customer operates. For a longstanding program such as RTP, there is very little validity to using this approach.

Figure 5: Evaluation Options for Non-Weather Sensitive Demand Response Programs



What remains, then, is a modeling exercise that will be described in the following section. Because RTP participants are exposed to a wide variety of prices by dint of being on the rate, the relationship between price signal and consumption can be estimated. By substituting the RTP price signal with the OAT price signal, a counterfactual reference load can be constructed.

One further complicating factor for the RTP evaluation concerns the inclusion of weather variables in both the ex post and ex ante regression modelling. For many individual customer regression methods, it is standard to use weather variables to explain variation in customer loads. However, because RTP day types are inherently dependent on weather – indeed defined by it – including weather as an explanatory variable in the regression can introduce confounding bias. That is, including weather variables in the model will misattribute the effect of the price signal to the change in weather, making the (incorrect) assumption that prices and weather are independent.

3 EVALUATION METHODOLOGY

Because of the long-standing RTP program option for commercial customers, and because the program is not dispatched on only a subset of days, the evaluation options to estimate load impacts are quite different than many other demand response programs. What is similar, however, is that in order to assess program impacts, we must construct load profiles for what the customer would have done had they not been on the RTP tariff. The appropriate counterfactual is the customer's consumption patterns on the otherwise applicable tariff (OAT). For example, a customer on the GS-2 RTP tariff would otherwise be metered on the standard GS2 tariff.

This counterfactual was modeled using a price model that estimates the relationship between the price each customer is exposed to and their load. From that model reference loads can be constructed by predicting what customers would have done on the OAT using individual customer regressions. Table 5 and Table 6 summarize our proposed approaches for the ex post and ex ante evaluations, respectively.

Table 5: Real-Time Pricing Ex post Approach

Methodology Component	Demand Side Analytics Approach
1. Population or sample analyzed	Analyze the full population of participants. Because most participants have been on the program for a long time, there is little available data from which to construct any comparison group. For that reason, we relied on individual customer regressions using a price model.
2. Data included in the analysis	All 2017-2019 data for participants
3. Use of control groups	Because of the uniqueness of the target population, we relied on a within-subjects method for developing ex post impacts.
4. Model selection	The final matching model is identified based on out-of-sample metrics for bias and fit. The process relies on splitting the dataset into training and testing data. The models are developed using the training data and applied, out-of-sample, to the testing data. For each of models specified, we produce standard metrics for bias and

Methodology Component	Demand Side Analytics Approach
	goodness of fit. The best model is identified by first narrowing the candidate models to the three with the least bias and then selecting the model with the highest precision.
5. Segmentation of impact results	The results are segmented by: ▪ Rate/Otherwise Applicable Tariff ▪ LCA ▪ Enabling technology (Y/N) ▪ Dual enrollment (by program) The main segment categories are building blocks. They are designed to ensure segment level results add up to the total and to enable production of ex ante impacts, including busbar level results. We also produced results for additional categories, such as industry type.

Ex ante impacts for the RTP program are straightforward. Leveraging the model estimated for each customer in the ex post analysis, both the predicted observed load and counterfactual reference load can be predicted using updated prices and weather scenarios.

Table 6: Real Time Pricing Ex Ante Approach

Methodology Component	Demand Side Analytics Approach
1. Years of historical performance used	At least two years of historical data will be used to estimate ex ante price response.
2. Process for producing ex ante impacts	The key steps will be: ▪ Collect data on the current or future RTP and OAT tariffs for each rate class ▪ Construct the price ratios associated with the ex ante rates ▪ Use the ex post model(s) –predict loads under ex ante weather and tariff conditions ▪ Combine the ex ante reference loads, percent reductions, and enrollment forecasts for each segment ▪ Aggregate to produce overall ex ante load impacts
3. Accounting for changes in the participant mix	Because the customer mix may evolve, changes in the participant mix need be accounted for developing forecasts of reduction capability under planning conditions. From the outset we produced a detailed segmentation – building blocks – so we are able to account for changes in the customer mix over the historical and forecast periods.
4. Producing busbar level impacts	The requirement to produce granular results for distribution planning is relatively recent. Because impacts are modeled using individual customer regressions, impacts can easily be aggregated to whatever level of granularity is required, including at the busbar level. Unless other information is provided, we will scale impacts proportionately for even participation changes across busbars according to the ex ante participation forecast.

3.1 OVERVIEW OF EVALUATION METHOD SELECTED

As discussed above, RTP impacts were modeled using individual customer regressions that related price variations on a tariff to changes in hourly consumption. The first step in performing this estimation is to determine the prices that customers face on an RTP and otherwise-applicable rate. Rates have several components that add up to what a customer must respond to in each hour. The approach taken for each category is summarized in Table 7.

Table 7: Rate Component and Approach

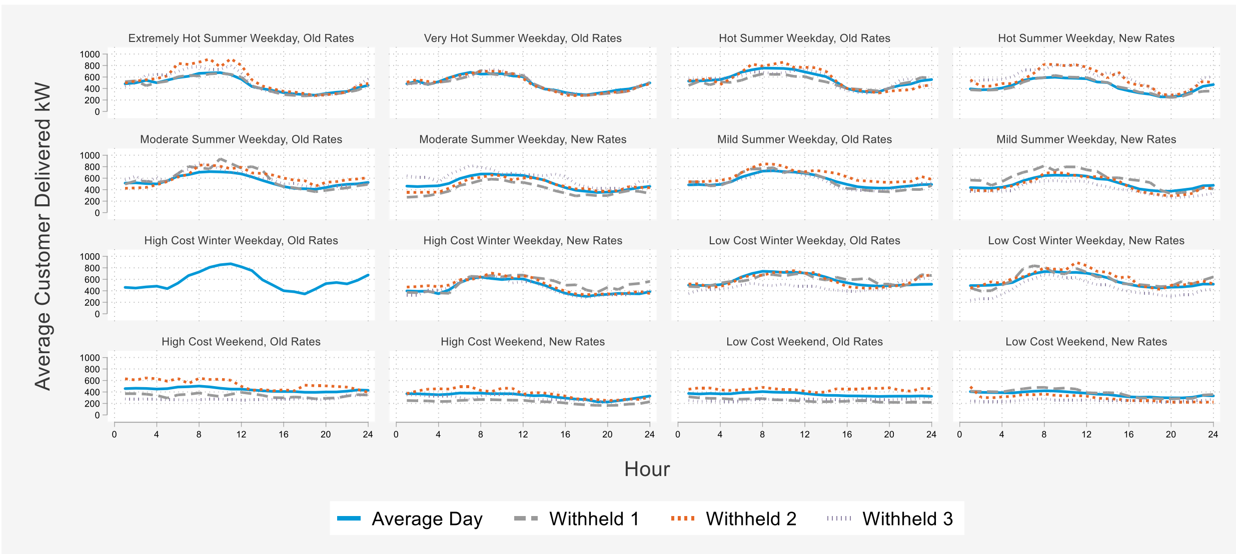
Cost Component	Category	Applies to	In Which Rate?	Approach
Delivery	Customer Charge	One-Time Monthly	Both	Ignore. This charge does not vary with consumption and is identical in both RTP and OAT
	Energy Charge	TOU Rate Blocks	Both	Multiply kWh consumed in each rate block by TOU price
	Demand Charge	Overall	Both	Convert to kWh equivalent by dividing by total hours in month and spreading out
	Demand Charge	TOU Rate Blocks	Both	Convert to kWh equivalent by dividing by total hours in each rate block by month and spreading out
Generation	RTP Energy Charge	Hourly (Variable)	RTP	Apply to hourly consumption in appropriate day type/hour
	OAT Energy Charge	TOU Rate Blocks	OAT	Multiply kWh consumed in each rate block by TOU price
	Demand Charge	Overall	OAT	Convert to kWh equivalent by dividing by total hours in month and spreading out
	Demand Charge	TOU Rate Blocks	OAT	Convert to kWh equivalent by dividing by total hours in each rate block by month and spreading out

Once each component has been normalized to an hourly per-kWh value, the components for either the RTP or OAT rates are summed.

OUT OF SAMPLE TESTING

To ensure that the model selected is accurately capturing the relationship between prices and consumption, each model was fitted on data that excluded three days of each RTP day type, and then used to predict consumption on those days. Because this year's model must capture load impacts under both old and new rate regimes, three days were randomly sampled from both regimes and for each RTP day type, for a total of 45 days. A comparison of the withheld days to the average day for RTP participants is shown in Figure 6. To ensure that the proxy days reflected recent load patterns, only dates from the summer of 2018 onwards were candidates for selection. No high cost winter weekdays were called between June 1, 2018 and the March 1, 2019 conversion to the new rate regime, so none could be selected as proxies. Days between March 1, 2019 and June 1, 2019 were explicitly excluded to avoid picking days when customers were transitioning to the new rates.

Figure 6: Comparison of Withheld Days to Average Day

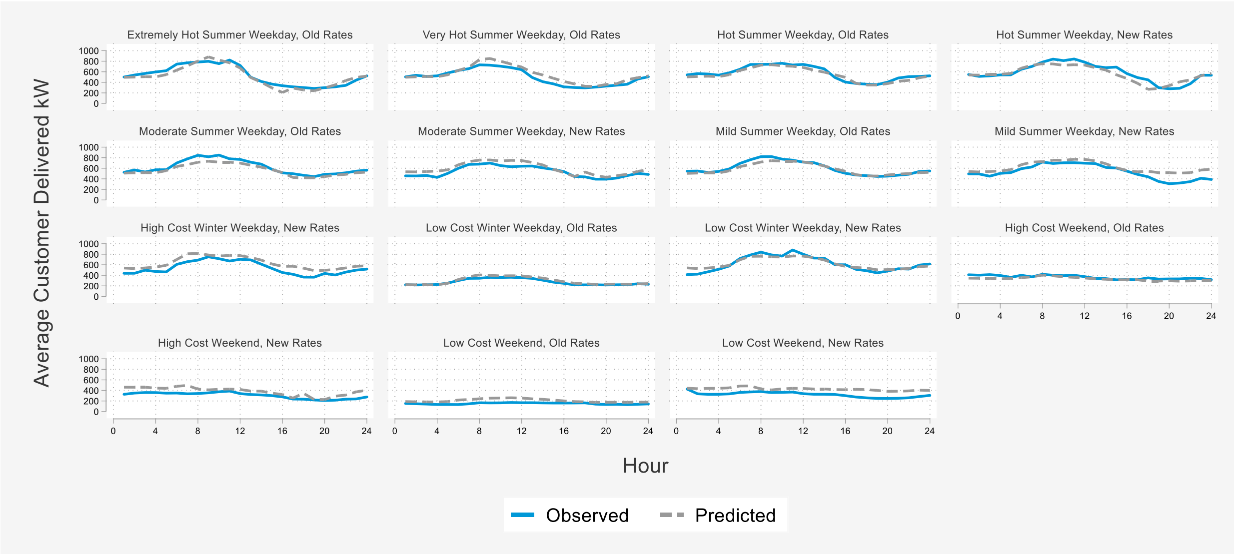


Ex Post Model

Nine different models were tested, including last year's model. As discussed at the end of Section 2.5, including weather variables in the regression models can introduce bias in the estimates – even for weather sensitive customers – and should be avoided. The best[1] model was then used to predict ex post loads on the withheld days. Figure 7 shows the predicted loads for each withheld day type. More detail, including a summary of model fit statistics, can be found in the appendix.

[1] Method for selecting best model is described in the appendix

Figure 7: Out of Sample Predictions on Withheld Days



The model specification is summarized in Equation 1.

Equation 1: Ex Post Regression

$$kW_{ih} = \alpha_{0h} + \beta_{1h} * price + \beta_{2h} * priceratio + \beta_{3h} * daytype + \beta_{4h} * month + \varepsilon_{ih}$$

Model Term	Description
kW_{ih}	Electricity delivered in kW for customer i, in hour h
α_0	Intercept
β_1	Regression coefficient for price a customer experiences in hour h
price	Hourly energy price inclusive of demand charges
β_2	Regression coefficient of the price ratio- captures load shifting
$priceratio$	Ratio of hourly price to daily maximum price for each customer
β_3	Regression coefficient accounting for variability in customer weekly schedules
$daytype$	Day of week
β_4	Regression coefficient accounting for variability in customer seasonal schedules
$month$	Month
ε_{ih}	Error term

Ex Ante Reference Load Model

The reference load model for ex ante was identical to that of ex post. Updated rates[2] were used to predict both the reference load (under the otherwise applicable tariff) and the expected observed load (under the RTP rate). Because no weather variables were included, the models only depend upon day type (weekday or weekend) and price signals to estimate variation in loads. Of course, as ex ante weather scenarios all have different weather conditions, small changes in temperature may categorize the average weekday or monthly peak day into different RTP day types, however the loads themselves do not depend upon daily weather conditions.

The priority for modeling ex ante reference loads is to realistically reflect what customers will do in the future. The California load impact protocols strongly suggest using multiple years of data to provide the model a wider range of weather and economic conditions from which to estimate the relationship of various factors to load changes. For the RTP program, however, no weather variables were included in the ex post model for the reasons outlined above. As such, variability in weather conditions are not applicable to producing ex ante reference loads. In the last year, RTP experienced a rate change that impacted customer consumption patterns. To assess whether there was validity to including customer load data from before the rate change, we reviewed the selected model's out of sample accuracy when the model was fit either using all three years of available data or only data from after the rate change went in to effect. The results of this analysis are summarized in Figure 8.

Figure 8: Model Out of Sample Fit based on Data Used

2 The rates used for ex ante modeling were taken from SCE's website as effective from January 1, 2020.

These results are quite consistent, with the model fit on new data only performing slightly better overall. The model fit on all data performs slightly better on the hot and moderate summer weekdays – important day types that drive ex ante August Peak Day impacts. This small and incremental improvement overall for the model fit with new data does appear to justify the exclusion of over two thirds of the available interval data from which to produce ex ante impacts, especially as the overall model seems to improve fit on key day types. For the ex ante analysis, all interval data was used.

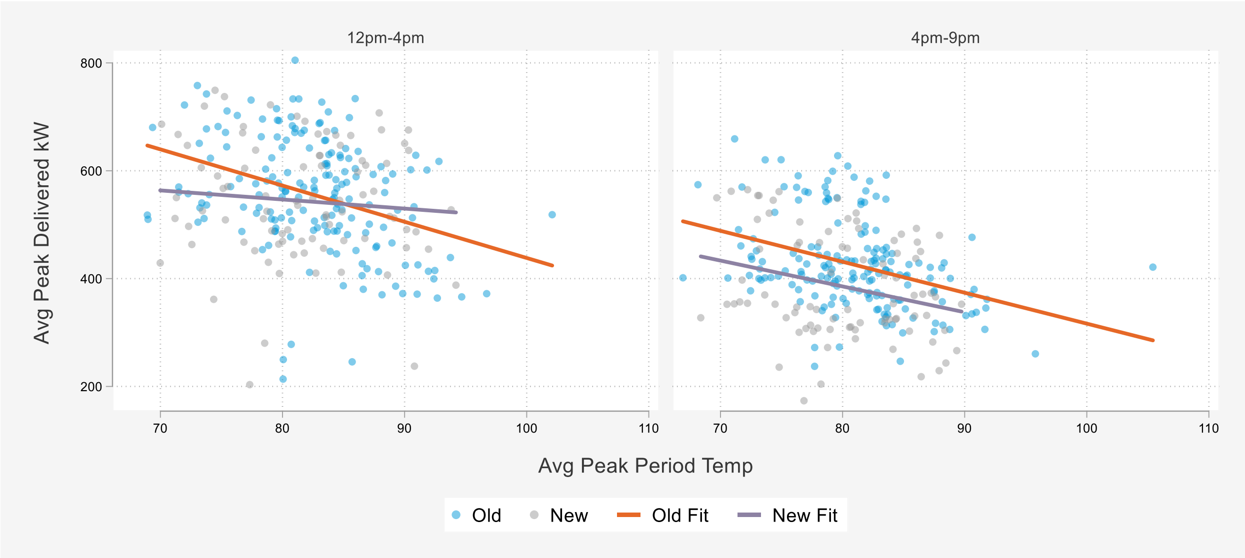
4 EX POST RESULTS

A challenge to the validity of any RTP modeling exercise is that because the loads on the otherwise applicable tariff are never observed, it is difficult to assess whether the counterfactual loads are reflective of what customers would have done. Out of sample testing is useful insofar as it assumes that customer price responses are consistent between the two tariffs and that there is no other confounding variable that is omitted from the model. In prior years, these assumptions were nearly impossible to test, because the RTP tariff remained essentially the same from year to year. This year, however, a completely new rate structure was introduced, allowing for several additional lines of inquiry. Prior to reviewing ex post results, we summarize the effects of the introduction of these new rates.

4.1 CONSUMPTION CHANGES ASSOCIATED WITH NEW RATE

A key question to answer in this year's evaluation in particular is whether there is evidence of customer response to the introduction of new rates in March of 2019. As discussed in the introductory sections of this report, the new rate structure was significantly different in several ways, including a narrower peak period and a shift in rate block hours and structure. To determine the extent to which customers were responding to new price signals, we investigated trends in raw load data for summer weekdays in 2018 and 2019, shown in Figure 9.

Figure 9: Peak Period Rate Shifting



Several insights can be gleaned from this figure.

- Customers in 2019 reduced their consumption in the 4pm-9pm window compared to 2018.
  - ✓ This reflects the higher RTP price that customers experienced in 2019 compared to those same hours in 2018, regardless of the RTP daytype.
- Regardless of RTP day type classification and its changes, customers exhibited the same downward trend in consumption in 4pm-9pm across both summers.
  - ✓ On hotter days, customers experience higher prices during the peak period. In response, they lower consumption during that period.
- Customers in 2018 had the same relationship between hotter days and lower loads during the 12pm-4pm window as during the 4pm-9pm window.
  - ✓ Because the peak period in 2018 was much broader relative to 2019, the same relationship between higher prices and lower loads on peak held.
- Customers in 2019 did not have a statistically significant negative relationship between hotter days and lower consumption in the 12pm-4pm window.
  - ✓ Because prices during the 12pm to 4pm window for customers under the new rate regime were much lower than the prices from 4pm-9pm, customers shifted consumption away from the 4pm-9pm window and towards the 12pm-4pm window.
  - ✓ The relationship between hotter days and consumption in the 12pm-4pm window in 2019 is relatively flat. On hotter days, RTP customers were shifting *more* load away from the peak period, both compared to the 2019 on-peak period and the 12pm-4pm period in the year before.

This is clear evidence that customers respond to the new price signals, regardless of modeling choices made.

4.2 OVERALL RESULTS

On the system peak day, 105 RTP customers delivered an average of 86.5kW (18.9%) impacts during the peak period (4pm-9pm). In aggregate, this was 8.83MW of load reduction during this time. In general, impacts are higher in the summer months compared to winter months, driven by high RTP peak period prices. During summer months, peak day impacts are higher than average weekday impacts, however the results are quite noisy and this difference should be interpreted with caution.

On the following pages, load profiles for the September 4th System Peak Day are shown. In general, loads are roughly equal until the peak period, at which point the observed load drops relative to the reference load. In the last hour of the peak period, impacts drop to zero as the reference load drops in that hour. This last-hour impact reversal is counterintuitive at first; however, upon investigation the result is logical. In hours ending 17 through 20 in Figure 10, the RTP rate is clearly higher, driven by the generation hourly RTP tariff. That tariff, however, does not distribute energy charges equally throughout the peak period. Instead, the RTP peak is even narrower than the 4pm-9pm TOU peak period. In the last hour of the peak period, the OAT rate driven by the TOU demand charges is in fact higher than the RTP rate. This effect occurs in all peak period results. As a result, all average 4pm-9pm peak period impacts have a zero or negative impact in the last hour of the period. As results shown in the remainder of this report are averaged across the peak period, this dampening effect should be kept front of mind.

Figure 10: Comparison of RTP and OAT on Hot Summer Weekdays

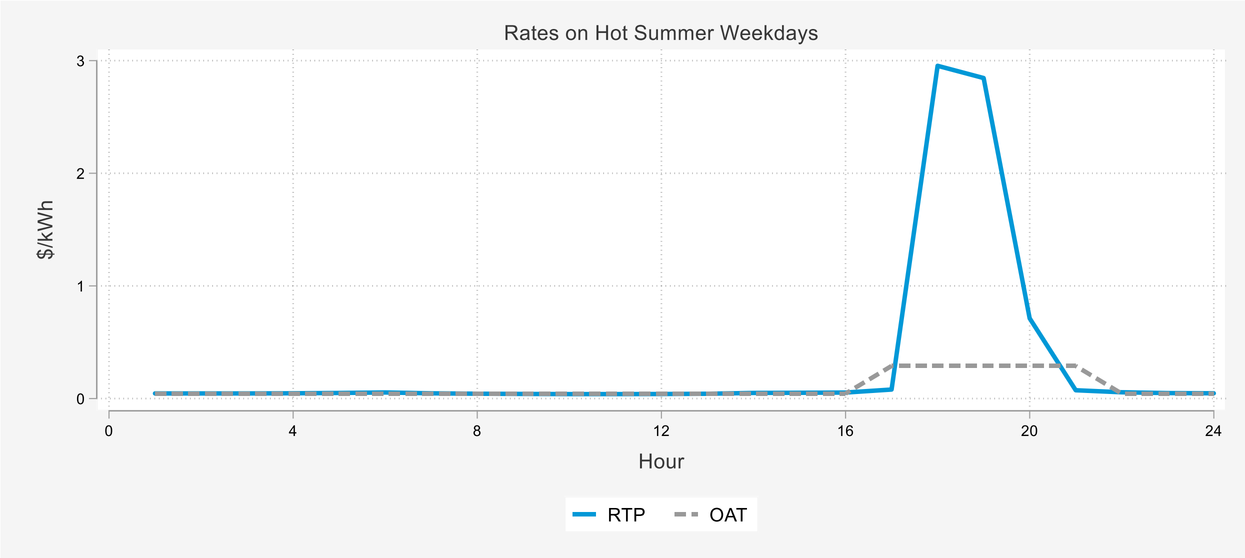


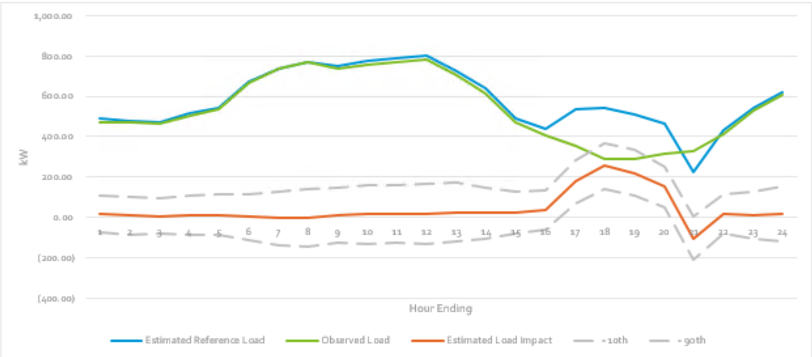
Table 8: Ex Post Impacts by Day Type for All Customers

Day Type	# Cust	Average Customer (kW) Ref. Load	Obs. Load	Impact	95% CI	% Impact	Agg. Impact (MW)
Jan - Average Weekday: Low Cost Winter Weekday (Old Rates)	104	226.59	223.49	3.11	-26.46 - 32.67	1.4	0.32
Jan - Monthly Peak Day: Low Cost Winter Weekday (Old Rates)	104	226.59	223.49	3.11	-26.46 - 32.67	1.4	0.32
Feb - Average Weekday: Low Cost Winter Weekday (Old Rates)	104	225.98	222.91	3.07	-23.70 - 29.85	1.4	0.32
Feb - Monthly Peak Day: Low Cost Winter Weekday (Old Rates)	104	225.98	222.91	3.07	-23.70 - 29.85	1.4	0.32
Mar - Average Weekday: Low Cost Winter Weekday (New Rates)	105	217.77	219.19	-1.43	-24.46 - 21.61	-0.7	-0.15
Mar - Monthly Peak Day: Low Cost Winter Weekday (New Rates)	104	219.86	218.42	1.44	-21.60 - 24.48	0.7	0.15
Apr - Average Weekday: Low Cost Winter Weekday (New Rates)	106	234.09	236.04	-1.95	-22.92 - 19.02	-0.8	-0.21
Apr - Monthly Peak Day: Low Cost Winter Weekday (New Rates)	106	234.09	236.04	-1.95	-22.92 - 19.02	-0.8	-0.21
May - Average Weekday: Low Cost Winter Weekday (New Rates)	102	508.62	499.26	9.36	-10.31 - 29.02	1.8	0.95
May - Monthly Peak Day: Low Cost Winter Weekday (New Rates)	98	527.88	518.11	9.76	-9.65 - 29.18	1.8	0.96
Jun - Average Weekday: Mild Summer Weekday (New Rates)	98	472.04	517.57	-45.52	-94.40 - 3.36	-9.6	-4.46
Jun - Monthly Peak Day: Hot Summer Weekday (New Rates)	98	472.04	331.35	140.69	91.81 - 189.57	29.8	13.79
Jul - Average Weekday: Mild Summer Weekday (New Rates)	102	472.24	514.06	-41.82	-85.38 - 1.74	-8.9	-4.27
Jul - Monthly Peak Day: Hot Summer Weekday (New Rates)	101	476.63	328.16	148.47	105.23 - 191.71	31.1	15.00
Aug - Average Weekday: Moderate Summer Weekday (New Rates)	101	472.30	464.97	7.33	-36.50 - 51.16	1.6	0.74
Aug - Monthly Peak Day: Moderate Summer Weekday (New Rates)	102	467.67	460.42	7.25	-37.98 - 52.48	1.6	0.74
Sept - Average Weekday: Moderate Summer Weekday (New Rates)	101	465.37	461.71	3.66	-44.13 - 51.45	0.8	0.37
Sept - Monthly Peak Day: Hot Summer Weekday (New Rates)	102	455.68	315.34	140.34	-25.52 - 306.19	30.8	14.31
Oct - Average Weekday: Low Cost Winter Weekday (New Rates)	100	530.44	520.59	9.86	-11.55 - 31.26	1.9	0.99
Oct - Monthly Peak Day: High Cost Winter Weekday (New Rates)	104	226.59	223.49	3.11	-26.46 - 32.67	1.4	0.32
Nov - Average Weekday: Low Cost Winter Weekday (Old Rates)	104	226.59	223.49	3.11	-26.46 - 32.67	1.4	0.32
Nov - Monthly Peak Day: Low Cost Winter Weekday (Old Rates)	104	225.98	222.91	3.07	-23.70 - 29.85	1.4	0.32
Dec - Average Weekday: Low Cost Winter Weekday (Old Rates)	104	225.98	222.91	3.07	-23.70 - 29.85	1.4	0.32
Dec - Monthly Peak Day: Low Cost Winter Weekday (Old Rates)	105	217.77	219.19	-1.43	-24.46 - 21.61	-0.7	-0.15

Figure 11: Average Customer Ex Post Impacts on September 4, 2019

Selection Options	
Reporting Level	Average Customer
Ex Post Daytype	Monthly Peak Day
Month	September
Customer Segment	All Customers

Event Characteristics	
# Dispatched	102
Daily Max Temp	95.6
Peak Period Impact (kW)	140.3
Date	September 4, 2019
RTP Daytype	Hot Summer Weekday (New Rates)



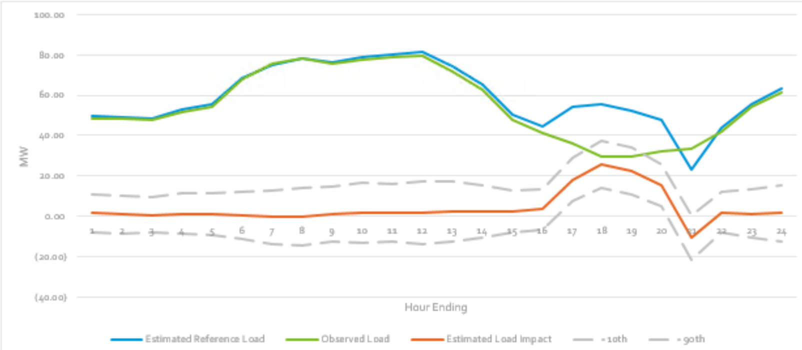
Hour Ending	Estimated Reference Load kW	Observed Load kW	Estimated Load Impact kW	Estimated Load Impact %	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	487.14	472.39	14.75	3%	77	(75.62)	(22.19)	14.75	51.68	105.11
2	479.18	471.49	7.69	2%	76	(83.86)	(29.73)	7.69	45.11	99.25
3	472.64	465.78	6.86	1%	76	(79.57)	(28.47)	6.86	42.19	93.30
4	515.70	503.33	12.37	2%	75	(85.87)	(27.78)	12.37	52.53	110.61
5	544.78	532.97	11.80	2%	75	(88.11)	(29.04)	11.80	52.64	111.72
6	668.88	666.74	2.14	0%	74	(112.00)	(44.51)	2.14	48.80	116.28
7	733.43	738.27	(4.85)	-1%	73	(136.85)	(58.80)	(4.85)	49.11	127.16
8	766.51	768.64	(2.13)	0%	73	(143.88)	(60.07)	(2.13)	55.81	139.62
9	749.91	739.04	10.87	1%	75	(123.72)	(44.14)	10.87	65.88	145.46
10	772.46	757.90	14.57	2%	79	(132.12)	(45.39)	14.57	74.52	161.26
11	787.37	771.41	15.96	2%	84	(124.90)	(41.62)	15.96	73.53	156.81
12	798.82	781.63	17.18	2%	88	(133.88)	(44.56)	17.18	78.93	168.25
13	725.90	701.14	24.76	3%	92	(120.85)	(34.76)	24.76	84.28	170.38
14	636.02	614.14	21.88	3%	94	(105.86)	(30.33)	21.88	74.10	149.63
15	493.20	469.88	23.31	5%	95	(78.30)	(18.22)	23.31	64.85	124.93
16	437.97	403.82	34.14	8%	96	(63.11)	(5.61)	34.14	73.90	131.40
17	533.02	354.63	178.39	33%	94	72.18	134.98	178.39	221.80	284.59
18	543.52	289.59	253.93	47%	90	139.39	207.12	253.93	300.75	368.48
19	509.71	289.51	220.20	43%	87	106.31	173.65	220.20	266.76	334.10
20	466.05	313.99	152.06	33%	85	51.30	110.88	152.06	193.25	252.83
21	226.07	328.98	(102.91)	-46%	84	(209.29)	(146.39)	(102.91)	(59.43)	3.47
22	430.64	413.28	17.36	4%	82	(81.19)	(22.92)	17.36	57.64	115.91
23	541.91	529.44	12.47	2%	80	(105.54)	(35.76)	12.47	60.71	130.49
24	619.10	603.91	15.19	2%	79	(121.40)	(40.64)	15.19	71.01	151.77

Daily	Daily Energy kWh	kWh	kWh Δ	%	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
Overall	13,939.94	12,981.91	958.03	7%	190	839.89	909.74	958.03	1,006.31	1,076.16
Peak Hours	2,278.38	1,576.70	701.68	31%	65	593.20	657.34	701.68	746.02	810.16

Figure 12: Aggregate Ex Post Impacts on September 4, 2019

Selection Options	
Reporting Level	Aggregate
Ex Post Daytype	Monthly Peak Day
Month	September
Customer Segment	All Customers

Event Characteristics	
# Dispatched	102
Daily Max Temp	95.6
Peak Period Impact (MW)	14.3
Date	September 4, 2019
RTP Daytype	Hot Summer Weekday (New Rates)



Hour Ending	Estimated Reference Load	Observed Load	Estimated Load Impact		Temp	Estimated Load Impact Range				
	MW	MW	MW	%	F	10th	30th	50th	70th	90th
1	49.69	48.18	1.50	3%	77	(7.71)	(2.26)	1.50	5.27	10.72
2	48.88	48.09	0.78	2%	76	(8.55)	(3.03)	0.78	4.60	10.12
3	48.21	47.51	0.70	1%	76	(8.12)	(2.90)	0.70	4.30	9.52
4	52.60	51.34	1.26	2%	75	(8.76)	(2.83)	1.26	5.36	11.28
5	55.57	54.36	1.20	2%	75	(8.99)	(2.96)	1.20	5.37	11.40
6	68.23	68.01	0.22	0%	74	(11.42)	(4.54)	0.22	4.98	11.86
7	74.81	75.30	(0.49)	-1%	73	(13.96)	(6.00)	(0.49)	5.01	12.97
8	78.18	78.40	(0.22)	0%	73	(14.68)	(6.13)	(0.22)	5.69	14.24
9	76.49	75.38	1.11	1%	75	(12.62)	(4.50)	1.11	6.72	14.84
10	78.79	77.31	1.49	2%	79	(13.48)	(4.63)	1.49	7.60	16.45
11	80.31	78.68	1.63	2%	84	(12.74)	(4.25)	1.63	7.50	16.00
12	81.48	79.73	1.75	2%	88	(13.66)	(4.55)	1.75	8.05	17.16
13	74.04	71.52	2.53	3%	92	(12.33)	(3.55)	2.53	8.60	17.38
14	64.87	62.64	2.23	3%	94	(10.80)	(3.09)	2.23	7.56	15.26
15	50.31	47.93	2.38	5%	95	(7.99)	(1.86)	2.38	6.61	12.74
16	44.67	41.19	3.48	8%	96	(6.44)	(0.57)	3.48	7.54	13.40
17	54.37	36.17	18.20	33%	94	7.36	13.77	18.20	22.62	29.03
18	55.44	29.54	25.90	47%	90	14.22	21.13	25.90	30.68	37.58
19	51.99	29.53	22.46	43%	87	10.84	17.71	22.46	27.21	34.08
20	47.54	32.03	15.51	33%	85	5.23	11.31	15.51	19.71	25.79
21	23.06	33.56	(10.50)	-46%	84	(21.35)	(14.93)	(10.50)	(6.06)	0.35
22	43.93	42.15	1.77	4%	82	(8.28)	(2.34)	1.77	5.88	11.82
23	55.28	54.00	1.27	2%	80	(10.76)	(3.65)	1.27	6.19	13.31
24	63.15	61.60	1.55	2%	79	(12.38)	(4.15)	1.55	7.24	15.48

Daily	Daily Energy					Estimated Energy Change				
	MWh	MWh	MWh Δ	%	ΣCDH (75)	10th	30th	50th	70th	90th
Overall	1,421.87	1,324.15	97.72	7%	190	(11,952.02)	(4,827.45)	97.72	5,022.89	12,147.46
Peak Hours	232.40	160.82	71.57	31%	65	(10,993.68)	(4,451.20)	71.57	4,594.34	11,136.82

4.3 RESULTS BY CATEGORY

The majority of impacts came from the [redacted], which delivered [redacted] of the 14.3MW from 4pm-9pm on the system peak day (September 4th, 2019). This was primarily due to [redacted]. Average reference loads were nearly [redacted] and peak period impacts were over [redacted]

Table 9: Ex Post Impacts by LCA on System Peak Day

LCA	# Enrolled	Average Customer (kW) Ref. Load	Obs. Load	Impact	95% CI	% Impact	Agg. Impact (MW)
Outside LA Basin	7	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Ventura	17	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
LA Basin	78	180.38	151.27	29.12	-3.03 - 61.27	16.1	2.27
All Customers	102	455.68	315.34	140.34	-25.52 - 306.19	30.8	14.31

In the zones affected by the San Onofre Nuclear Generating Station (SONGS), customers delivered [redacted] of load reduction during the full event hours. [redacted], who delivered on average [redacted] of load relief per participant. In aggregate, these customers delivered [redacted] of the total load shed despite representing just 17% of the total population.

Table 10: Ex Post Impacts by Zone

Size	# Enrolled	Average Customer (kW) Ref. Load	Obs. Load	Impact	95% CI	% Impact	Agg. Impact (MW)
South Orange County	13	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
South of Lugo	17	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Remainder of System	72	193.68	175.80	17.88	-615.22 - 650.97	9.2	1.29
All Customers	102	455.68	315.34	140.34	-25.52 - 306.19	30.8	14.31

RTP customers were segmented into size categories based on maximum demand over the prior summer. The results for each category are reported below. As expected, larger customers had higher reference loads with more available load to shed. They also delivered a higher percent impact (nearly 31%) than the smaller customers, essentially providing all aggregate impacts associated with this day.

Table 11: Ex Post Impacts by Customer Size

Size	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
20kW or Lower	16	XXX	XXX	XXX	XXX	XXX	XXX
20-200kW	13	XXX	XXX	XXX	XXX	XXX	XXX
Greater than 200kW	73	634.73	438.71	196.02	-8.94 - 400.97	30.9	14.31
All Customers	102	455.68	315.34	140.34	-25.52 - 306.19	30.8	14.31

Eleven customers were on RTP with enabling technology. [redacted]

Table 12: Ex Post Impacts by AutoDR Status

AutoDR Status	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
Yes	11	XXX	XXX	XXX	XXX	XXX	XXX
No	91	XXX	XXX	XXX	XXX	XXX	XXX
All Customers	102	455.68	315.34	140.34	-25.52 - 306.19	30.8	14.31

4.4 COMPARISON TO PRIOR YEAR

As discussed above, comparisons to the prior year's results are difficult to observe because of the magnitude of the changes to the RTP rate. Because RTP day type dispatch criteria changed, simply comparing performance on 'Hot Summer Weekdays' between 2018 and 2019 would not be appropriate. Table 13 summarizes the difference in day type definition between the old and new rate regimes. The three columns on the left show the number of day types reported under the definitions that applied at the time – for example the 2018 event days used the day type definitions that were in use in 2018. The right three columns show what the day type frequency would have been had the day type definitions never been updated. The primary columns to focus on are the PY2019 counts for both the old and new definitions.

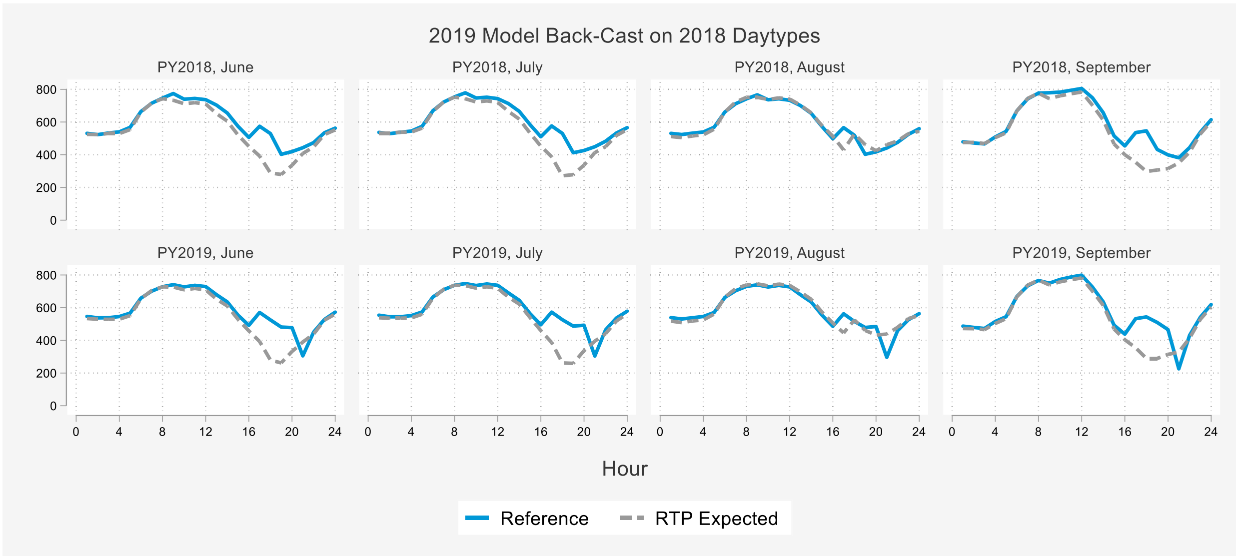
Table 13: Distribution of Event Types by Method

Day Type	Using Contemporary Definitions			Using Consistent (Old) Definitions		
	PY2017	PY2018	PY2019	PY2017	PY2018	PY2019
Extremely Hot Summer Weekday	3	6		3	6	7
Very Hot Summer Weekday	8	4		8	4	8
Hot Summer Weekday	22	25	10	22	25	23
Moderate Summer Weekday	25	18	43	25	18	15
Mild Summer Weekday	23	28	27	23	28	27
High Cost Winter Weekday	9	2	5	9	2	5
Low Cost Winter Weekday	161	168	165	161	168	165
High Cost Weekend	25	20	15	25	20	15
Low Cost Weekend	47	52	58	47	52	58

A few things are clear from this table. First, there were some days hot enough in 2019 such that they would have been considered either 'Extremely Hot' or 'Very Hot' summer weekdays, had those categories not been eliminated. Second, because of the shift in criteria for 'Hot' and 'Moderate' summer weekdays between the two rate regimes, the relative frequency of these two day types shift between the two categorization methods.

Nevertheless, we investigated the impact of the change in RTP rates on program impacts. Using the 2019 model specification we produced results for the 2019 summer assuming that the historic tariffs applied. Similar, though not identical, results were found for the expected RTP rates, with the biggest differences in predicted loads coming in hours 14-16. This is consistent with the change in RTP peak period from 1pm-6pm to 4pm-9pm. The OAT reference loads changed moderately, with increasing loads occurring earlier in the afternoon coincident with the old peak periods. However as always, the RTP day type for a given day has a much larger impact on program impacts than any other program change.

Figure 13: Comparison of Ex Post Results using Old and New Rate Regimes



4.5 KEY FINDINGS

RTP delivered 14.3MW of load relief during the 4pm-9pm peak period. The largest concentrations of impacts and participants were among large customers and concentrated in the Outside LA LCA.

Two observations are key takeaways from this analysis. First, a comparison of the raw data shows a clear shift in participant consumption patterns with the introduction to the new rate and rate blocks. Second, this rate block shift had a dampening effect on the last hour of the peak period impacts, when the OAT rate was in fact higher than the RTP rate.

5 EX ANTE RESULTS

This section summarizes the results of the ex ante impact estimation process for RTP from 2020 to 2030.

5.1 ENROLLMENT FORECAST

RTP enrollment is expected to decline from the 102 participants enrolled at the end of Summer 2019 to 102 in August of 2020, with an expected loss of eight service accounts per year until 2024 when the program stabilizes.

Table 14: RTP Ex Ante Enrollment Forecast

Program/Portfolio	2020	2021	2022	2023	2024	2025	2026-2030
Program	102	94	86	78	70	70	70
Portfolio	79	73	66	60	54	54	54

5.2 OVERALL RESULTS

Once the RTP program reaches a steady state in 204 with constant, aggregate August Peak Day impacts will be 15MW, shown in Table 15. Per the ex post modeling, no weather variables are included in the ex ante specification, so the only difference between these scenarios is the RTP day type associated with the CAISO and SCE 1-in-2 and 1-in-10 weather scenarios. All August Monthly Peak days are associated with the 'Hot Summer Weekday' RTP day type and have the same rate schedule applied. Finally, the decrease in impacts over time is attributable to a decline in program enrollment over the forecast horizon.

Table 15: RTP Aggregate Program Ex Ante Impacts - August Peak Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2020	21.86	21.86	21.86	21.86
2021	20.15	20.15	20.15	20.15
2022	18.43	18.43	18.43	18.43
2023	16.72	16.72	16.72	16.72
2024	15.00	15.00	15.00	15.00
2025	15.00	15.00	15.00	15.00
2026	15.00	15.00	15.00	15.00
2027	15.00	15.00	15.00	15.00
2028	15.00	15.00	15.00	15.00
2029	15.00	15.00	15.00	15.00
2030	15.00	15.00	15.00	15.00

Load impacts also vary by month, as weather patterns change the mix of RTP day types that are dispatched in the ex ante scenario. Shown in Table 16 are the average customer impacts for a monthly peak day. Impacts are highest in June through September when the summer RTP rates provide the most contrast with the otherwise applicable tariff. In some cases, such as June, the difference between an average (1-in-2) year compared to an extreme (1-in-10) year are enough to move shift the RTP day type customers are subjected to. In those cases, impacts can increase significantly.

Table 16: RTP Average Customer Program Ex Ante Impacts - By Monthly Peak Day

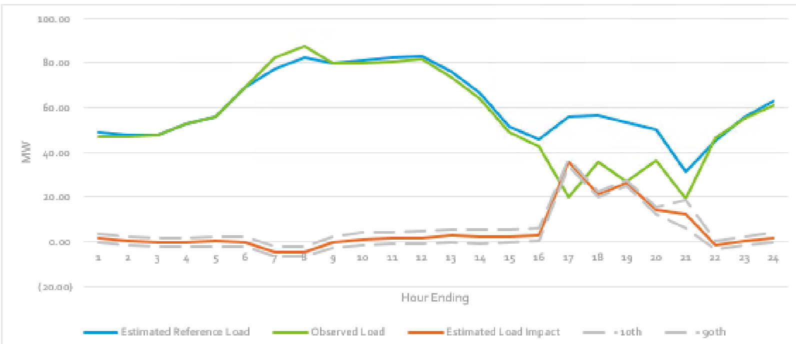
Day Type	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
January Peak Day	15.58	15.58	15.58	15.58
February Peak Day	13.03	13.03	13.03	13.03
March Peak Day	25.59	27.60	25.59	27.60
April Peak Day	26.72	28.65	26.72	28.65
May Peak Day	26.78	28.68	26.78	28.68
June Peak Day	44.67	212.14	44.67	212.14
July Peak Day	216.74	216.74	216.74	216.74
August Peak Day	214.34	214.34	214.34	214.34
September Peak Day	207.70	207.70	207.70	207.70
October Peak Day	27.66	27.66	27.66	27.66
November Peak Day	15.10	15.10	14.52	15.10
December Peak Day	13.02	13.02	13.02	13.02

The following figures show the results on an August monthly peak day under the four different weather scenarios.

Figure 14: Program Aggregate Ex Ante Impacts for SCE 1-in-2 August Peak Day

Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Monthly System Peak Day
Month	August
Weather Year	SCE 1-in-2
Forecast Year	2020

Event Characteristics	
On Peak Hours	4pm-9pm
# Enrolled	102
Daily Max Temp	92.3
MW Impact On Peak	21.9
% Impact On Peak	44.2%
RTP Daytype	Hot Summer Weekday



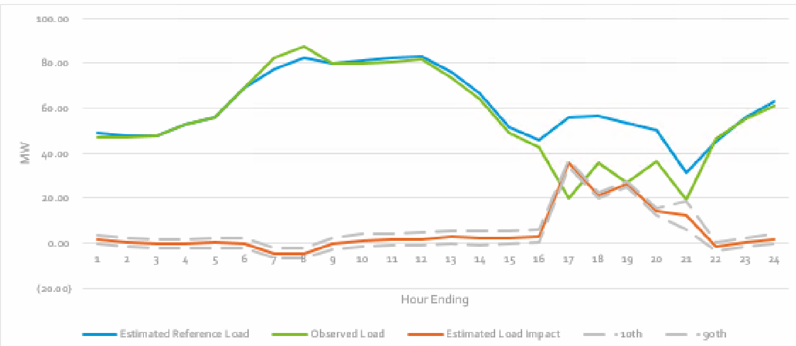
Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	48.75	47.03	1.72	77.5	(0.19)	0.94	1.72	2.50	3.62
2	47.80	47.40	0.40	76.4	(1.45)	(0.36)	0.40	1.15	2.24
3	47.74	47.78	(0.04)	75.6	(1.90)	(0.80)	(0.04)	0.72	1.82
4	52.58	52.59	(0.01)	74.6	(1.88)	(0.77)	(0.01)	0.75	1.85
5	56.10	55.99	0.11	73.9	(1.88)	(0.70)	0.11	0.92	2.10
6	69.47	69.47	(0.00)	73.4	(2.12)	(0.87)	(0.00)	0.86	2.11
7	77.69	82.19	(4.49)	72.8	(6.68)	(5.39)	(4.49)	(3.60)	(2.30)
8	82.69	87.30	(4.61)	72.8	(6.87)	(5.54)	(4.61)	(3.69)	(2.35)
9	79.74	80.16	(0.42)	74.7	(2.85)	(1.42)	(0.42)	0.57	2.01
10	80.95	79.69	1.26	78.7	(1.39)	0.18	1.26	2.35	3.92
11	82.18	80.59	1.58	82.9	(1.11)	0.48	1.58	2.68	4.28
12	83.36	81.62	1.75	86.4	(0.97)	0.64	1.75	2.86	4.47
13	76.00	73.43	2.57	88.8	(0.52)	1.30	2.57	3.83	5.65
14	66.63	64.30	2.33	90.9	(0.97)	0.98	2.33	3.67	5.63
15	51.71	49.19	2.52	92.3	(0.61)	1.24	2.52	3.79	5.64
16	45.92	42.76	3.16	92.2	0.24	1.97	3.16	4.35	6.08
17	55.66	20.21	35.45	91.5	34.03	34.87	35.45	36.03	36.87
18	56.88	35.53	21.35	90.0	20.07	20.83	21.35	21.88	22.64
19	53.19	27.08	26.11	88.6	24.76	25.56	26.11	26.66	27.46
20	50.09	36.13	13.96	86.9	12.50	13.36	13.96	14.55	15.41
21	31.53	19.08	12.45	83.4	6.06	9.84	12.45	15.05	18.83
22	44.94	46.47	(1.54)	80.4	(3.45)	(2.32)	(1.54)	(0.75)	0.38
23	56.11	55.59	0.52	78.5	(1.45)	(0.28)	0.52	1.32	2.49
24	63.10	61.24	1.85	77.0	(0.14)	1.04	1.85	2.67	3.85

Daily	MWh	Daily Energy MWh	MWh Δ	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
Overall	1,460.79	1,342.85	117.95	168	115.38	116.89	117.95	119.00	120.51
Peak Hours	247.35	138.04	109.31	65	106.20	108.04	109.31	110.59	112.42

Figure 15: Program Aggregate Ex Ante Impacts for SCE 1-in-10 August Peak Day

Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Monthly System Peak Day
Month	August
Weather Year	SCE 1-in-10
Forecast Year	2020

Event Characteristics	
On Peak Hours	4pm-9pm
# Enrolled	102
Daily Max Temp	95.4
MW Impact On Peak	21.9
% Impact On Peak	44.2%
RTP Daytype	Hot Summer Weekday

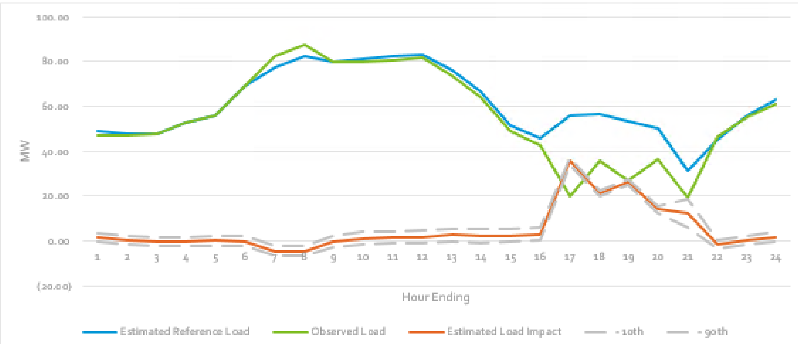


Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	48.75	47.03	1.72	78.1	(0.19)	0.94	1.72	2.50	3.62
2	47.80	47.40	0.40	77.0	(1.45)	(0.36)	0.40	1.15	2.24
3	47.74	47.78	(0.04)	76.0	(1.90)	(0.80)	(0.04)	0.72	1.82
4	52.58	52.59	(0.01)	74.7	(1.88)	(0.77)	(0.01)	0.75	1.85
5	56.10	55.99	0.11	73.7	(1.88)	(0.70)	0.11	0.92	2.10
6	69.47	69.47	(0.00)	73.0	(2.12)	(0.87)	(0.00)	0.86	2.11
7	77.69	82.19	(4.49)	72.2	(6.68)	(5.39)	(4.49)	(3.60)	(2.30)
8	82.69	87.30	(4.61)	72.1	(6.87)	(5.54)	(4.61)	(3.69)	(2.35)
9	79.74	80.16	(0.42)	74.6	(2.85)	(1.42)	(0.42)	0.57	2.01
10	80.95	79.69	1.26	79.5	(1.39)	0.18	1.26	2.35	3.92
11	82.18	80.59	1.58	84.9	(1.11)	0.48	1.58	2.68	4.28
12	83.36	81.62	1.75	88.6	(0.97)	0.64	1.75	2.86	4.47
13	76.00	73.43	2.57	90.2	(0.52)	1.30	2.57	3.83	5.65
14	66.63	64.30	2.33	91.9	(0.97)	0.98	2.33	3.67	5.63
15	51.71	49.19	2.52	93.7	(0.61)	1.24	2.52	3.79	5.64
16	45.92	42.76	3.16	95.4	0.24	1.97	3.16	4.35	6.08
17	55.66	20.21	35.45	95.3	34.03	34.87	35.45	36.03	36.87
18	56.88	35.53	21.35	94.9	20.07	20.83	21.35	21.88	22.64
19	53.19	27.08	26.11	93.5	24.76	25.56	26.11	26.66	27.46
20	50.09	36.13	13.96	90.5	12.50	13.36	13.96	14.55	15.41
21	31.53	19.08	12.45	87.0	6.06	9.84	12.45	15.05	18.83
22	44.94	46.47	(1.54)	83.9	(3.45)	(2.32)	(1.54)	(0.75)	0.38
23	56.11	55.59	0.52	81.3	(1.45)	(0.28)	0.52	1.32	2.49
24	63.10	61.24	1.85	79.9	(0.14)	1.04	1.85	2.67	3.85
Daily	**MWh**	**Daily Energy MWh**	**MWh Δ**	**ΣCDH (75)**	**Estimated Energy Change 10th**	**30th**	**50th**	**70th**	**90th**
Overall	1,460.79	1,342.85	117.95	212	115.38	116.89	117.95	119.00	120.51
Peak Hours	247.35	138.04	109.31	86	106.20	108.04	109.31	110.59	112.42

Figure 16: Program Aggregate Ex Ante Impacts for CAISO 1-in-2 August Peak Day

Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Monthly System Peak Day
Month	August
Weather Year	CAISO 1-in-2
Forecast Year	2020

Event Characteristics	
On Peak Hours	4pm-9pm
# Enrolled	102
Daily Max Temp	92.5
MW Impact On Peak	21.9
% Impact On Peak	44.2%
RTP Daytype	Hot Summer Weekday



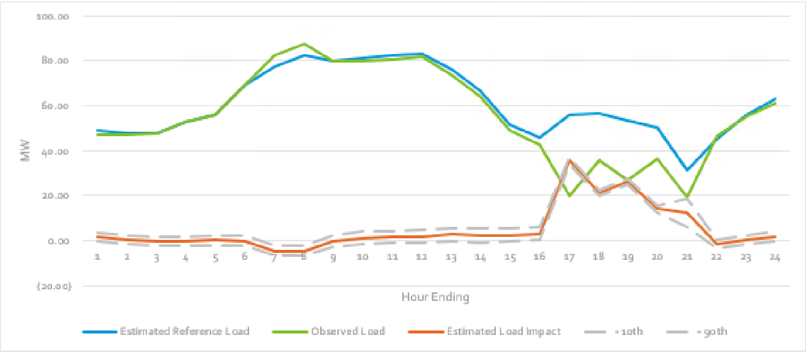
Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	48.75	47.03	1.72	78.0	(0.19)	0.94	1.72	2.50	3.62
2	47.80	47.40	0.40	77.0	(1.45)	(0.36)	0.40	1.15	2.24
3	47.74	47.78	(0.04)	76.2	(1.90)	(0.80)	(0.04)	0.72	1.82
4	52.58	52.59	(0.01)	75.4	(1.88)	(0.77)	(0.01)	0.75	1.85
5	56.10	55.99	0.11	74.7	(1.88)	(0.70)	0.11	0.92	2.10
6	69.47	69.47	(0.00)	74.1	(2.12)	(0.87)	(0.00)	0.86	2.11
7	77.69	82.19	(4.49)	73.5	(6.68)	(5.39)	(4.49)	(3.60)	(2.30)
8	82.69	87.30	(4.61)	73.5	(6.87)	(5.54)	(4.61)	(3.69)	(2.35)
9	79.74	80.16	(0.42)	75.5	(2.85)	(1.42)	(0.42)	0.57	2.01
10	80.95	79.69	1.26	79.6	(1.39)	0.18	1.26	2.35	3.92
11	82.18	80.59	1.58	83.8	(1.11)	0.48	1.58	2.68	4.28
12	83.36	81.62	1.75	87.7	(0.97)	0.64	1.75	2.86	4.47
13	76.00	73.43	2.57	90.4	(0.52)	1.30	2.57	3.83	5.65
14	66.63	64.30	2.33	92.0	(0.97)	0.98	2.33	3.67	5.63
15	51.71	49.19	2.52	92.5	(0.61)	1.24	2.52	3.79	5.64
16	45.92	42.76	3.16	92.3	0.24	1.97	3.16	4.35	6.08
17	55.66	20.21	35.45	91.6	34.03	34.87	35.45	36.03	36.87
18	56.88	35.53	21.35	89.5	20.07	20.83	21.35	21.88	22.64
19	53.19	27.08	26.11	87.5	24.76	25.56	26.11	26.66	27.46
20	50.09	36.13	13.96	85.7	12.50	13.36	13.96	14.55	15.41
21	31.53	19.08	12.45	83.0	6.06	9.84	12.45	15.05	18.83
22	44.94	46.47	(1.54)	81.0	(3.45)	(2.32)	(1.54)	(0.75)	0.38
23	56.11	55.59	0.52	79.8	(1.45)	(0.28)	0.52	1.32	2.49
24	63.10	61.24	1.85	78.7	(0.14)	1.04	1.85	2.67	3.85

Daily	Daily Energy MWh	MWh	MWh Δ	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
Overall	1,460.79	1,342.85	117.95	177	115.38	116.89	117.95	119.00	120.51
Peak Hours	247.35	138.04	109.31	62	106.20	108.04	109.31	110.59	112.42

Figure 17: Program Aggregate Ex Ante Impacts for CAISO 1-in-10 August Peak Day

Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Monthly System Peak Day
Month	August
Weather Year	CAISO 1-in-10
Forecast Year	2020

Event Characteristics	
On Peak Hours	4pm-9pm
# Enrolled	102
Daily Max Temp	94.6
MW Impact On Peak	21.9
% Impact On Peak	44.2%
RTP Daytype	Hot Summer Weekday



Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	48.75	47.03	1.72	75.5	(0.19)	0.94	1.72	2.50	3.62
2	47.80	47.40	0.40	74.6	(1.45)	(0.36)	0.40	1.15	2.24
3	47.74	47.78	(0.04)	74.0	(1.90)	(0.80)	(0.04)	0.72	1.82
4	52.58	52.59	(0.01)	73.3	(1.88)	(0.77)	(0.01)	0.75	1.85
5	56.10	55.99	0.11	72.6	(1.88)	(0.70)	0.11	0.92	2.10
6	69.47	69.47	(0.00)	71.9	(2.12)	(0.87)	(0.00)	0.86	2.11
7	77.69	82.19	(4.49)	71.5	(6.68)	(5.39)	(4.49)	(3.60)	(2.30)
8	82.69	87.30	(4.61)	71.2	(6.87)	(5.54)	(4.61)	(3.69)	(2.35)
9	79.74	80.16	(0.42)	73.6	(2.85)	(1.42)	(0.42)	0.57	2.01
10	80.95	79.69	1.26	77.6	(1.39)	0.18	1.26	2.35	3.92
11	82.18	80.59	1.58	82.5	(1.11)	0.48	1.58	2.68	4.28
12	83.36	81.62	1.75	87.3	(0.97)	0.64	1.75	2.86	4.47
13	76.00	73.43	2.57	90.8	(0.52)	1.30	2.57	3.83	5.65
14	66.63	64.30	2.33	93.6	(0.97)	0.98	2.33	3.67	5.63
15	51.71	49.19	2.52	94.6	(0.61)	1.24	2.52	3.79	5.64
16	45.92	42.76	3.16	94.6	0.24	1.97	3.16	4.35	6.08
17	55.66	20.21	35.45	94.2	34.03	34.87	35.45	36.03	36.87
18	56.88	35.53	21.35	93.4	20.07	20.83	21.35	21.88	22.64
19	53.19	27.08	26.11	91.8	24.76	25.56	26.11	26.66	27.46
20	50.09	36.13	13.96	89.3	12.50	13.36	13.96	14.55	15.41
21	31.53	19.08	12.45	85.2	6.06	9.84	12.45	15.05	18.83
22	44.94	46.47	(1.54)	82.3	(3.45)	(2.32)	(1.54)	(0.75)	0.38
23	56.11	55.59	0.52	80.9	(1.45)	(0.28)	0.52	1.32	2.49
24	63.10	61.24	1.85	79.5	(0.14)	1.04	1.85	2.67	3.85
Daily	MWh	Daily Energy MWh	MWh Δ	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
Overall	1,460.79	1,342.85	117.95	193	115.38	116.89	117.95	119.00	120.51
Peak Hours	247.35	138.04	109.31	79	106.20	108.04	109.31	110.59	112.42

5.3 RESULTS BY CATEGORY

As in the ex post results, the majority of ex ante impacts will come from the [redacted]

Table 17: RTP Aggregate Program Ex Ante Impacts - Typical Event Day by LCA

LCA	Weather Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Big Creek/ Ventura	CAISO 1-in-10	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
	CAISO 1-in-2	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
	SCE 1-in-10	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
	SCE 1-in-2	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
LA Basin	CAISO 1-in-10	2.46	2.27	2.09	1.90	1.68	1.68	1.68	1.68	1.68	1.68	1.68
	CAISO 1-in-2	2.46	2.27	2.09	1.90	1.68	1.68	1.68	1.68	1.68	1.68	1.68
	SCE 1-in-10	2.46	2.27	2.09	1.90	1.68	1.68	1.68	1.68	1.68	1.68	1.68
	SCE 1-in-2	2.46	2.27	2.09	1.90	1.68	1.68	1.68	1.68	1.68	1.68	1.68
Outside	CAISO 1-in-10	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
	CAISO 1-in-2	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
	SCE 1-in-10	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
	SCE 1-in-2	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

5.4 COMPARISON TO PRIOR YEAR

As with the ex post analysis, comparisons between the PY2018 and PY2019 results are challenging due to the extent of the rate changes. An important note is that while it was known that rates would be changing in the upcoming year, the new rate schedules had not yet been finalized prior to the completion of last year's evaluation. The PY2018 evaluators therefore estimated ex ante impacts using the old rate scheme with the caveat that the true ex ante results could be substantially different. In addition to the rate change, the ex ante weather forecasts were also updated in 2019. Disentangling the effects of both the rate change and weather change is complex, however, some key conclusions can be drawn. Table 18 shows the two changes associated with RTP day types forecasted for ex ante. Three sets of columns are shown: the historic ex ante RTP day types for each monthly peak day, then the RTP day types if just the ex ante weather had changed but the rate structure had stayed the same, then finally the update for both weather and rate change.

As a result of the ex ante weather update, the general trend was for an increase in the severity of RTP day type assigned to the same monthly peak day. This is consistent with the new ex ante weather being hotter, especially in July, August, and September, than the prior forecast. Because there were fewer summer weekday RTP day types in the new rate schedules, less variation in RTP day types for summer monthly peak days exist in the new regime as well. As a result, ex ante impacts are more consistent from month to month in the new regime since many monthly peak days share the same assigned RTP day type.

Another substantial change that occurred between last year and this year's evaluation is the change in program participants as shown earlier in Figure 4. Due to a relatively hot 2018 summer, customers experienced high bills on the RTP program and subsequently de-enrolled. The customers who remained on the program are likely to be different in terms of their ability to respond to the new price signals.

Table 18: Change in RTP Day Types for Ex Ante Monthly Peak Days

		PY2018 Monthly Peak Day Day Types		PY2019 Monthly Peak Day Back-Cast to PY2018 Day Types		PY2019 Monthly Peak Day in PY2019 Day Types	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
SCE	Jan	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday
	Feb	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday
	Mar	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday
	Apr	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday
	May	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday
	Jun	Moderate Summer Weekday	Moderate Summer Weekday	Moderate Summer Weekday	Extremely Hot Summer Weekday	Moderate Summer Weekday	Hot Summer Weekday
	Jul	Moderate Summer Weekday	Very Hot Summer Weekday	Very Hot Summer Weekday	Extremely Hot Summer Weekday	Hot Summer Weekday	Hot Summer Weekday
	Aug	Hot Summer Weekday	Hot Summer Weekday	Extremely Hot Summer Weekday	Extremely Hot Summer Weekday	Hot Summer Weekday	Hot Summer Weekday
	Sep	Moderate Summer Weekday	Extremely Hot Summer Weekday	Extremely Hot Summer Weekday	Extremely Hot Summer Weekday	Hot Summer Weekday	Hot Summer Weekday
	Oct	Low Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday
	Nov	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday
	Dec	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday
CAISO	Jan	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday
	Feb	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday
	Mar	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday
	Apr	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday
	May	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday
	Jun	Moderate Summer Weekday	Hot Summer Weekday	Moderate Summer Weekday	Extremely Hot Summer Weekday	Moderate Summer Weekday	Hot Summer Weekday
	Jul	Hot Summer Weekday	Hot Summer Weekday	Very Hot Summer Weekday	Very Hot Summer Weekday	Hot Summer Weekday	Hot Summer Weekday
	Aug	Very Hot Summer Weekday	Very Hot Summer Weekday	Extremely Hot Summer Weekday	Extremely Hot Summer Weekday	Hot Summer Weekday	Hot Summer Weekday
	Sep	Hot Summer Weekday	Extremely Hot Summer Weekday	Extremely Hot Summer Weekday	Extremely Hot Summer Weekday	Hot Summer Weekday	Hot Summer Weekday
	Oct	Low Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday	High Cost Winter Weekday
	Nov	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday	Low Cost Winter Weekday	High Cost Winter Weekday
	Dec	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday	Low Cost Winter Weekday

Separately, an analysis was performed to assess the comparability of last year's ex ante impacts with this year. The results show directionally appropriate impacts as last year's ex ante weather was cooler than this year's resulting in less extreme RTP price schedules for each month.

Table 19: 1pm-6pm Impacts for 2018 Rates using 2019 Specification – SCE 1-in-2 Peak Day

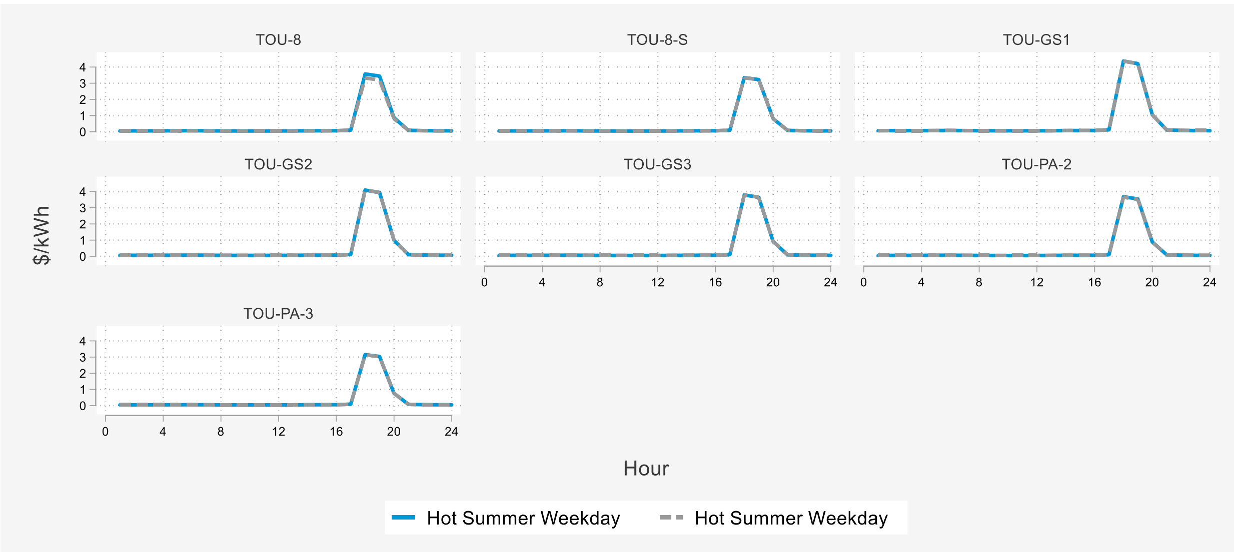
Month	Predicted Loads		Price			Impact	
	OAT	RTP	OAT	RTP	Ratio	kW	%
January	682.7	668.6	$ 0.11	$ 0.11	1.03	14.1	2.1
February	678.0	664.2	$ 0.11	$ 0.11	1.03	13.8	2.0
March	666.6	650.1	$ 0.11	$ 0.11	1.02	16.5	2.5
April	664.1	647.8	$ 0.11	$ 0.11	1.02	16.4	2.5
May	653.1	636.9	$ 0.11	$ 0.11	1.02	16.2	2.5
June	641.2	620.7	$ 0.30	$ 0.14	0.47	20.5	3.2
July	631.0	562.8	$ 0.27	$ 1.00	3.71	68.2	10.8
August	626.0	506.2	$ 0.28	$ 2.30	8.29	119.8	19.1
September	616.5	500.6	$ 0.29	$ 2.30	7.99	115.8	18.8
October	619.0	577.3	$ 0.11	$ 0.34	3.18	41.7	6.7
November	637.6	623.7	$ 0.11	$ 0.11	1.02	14.0	2.2
December	634.1	620.9	$ 0.11	$ 0.11	1.03	13.2	2.1

Nevertheless, last year's peak period impact for a September monthly peak day was reported as approximately 34%, compared to 19% in the modeling above. This difference appears to be attributed to the ex ante modeling itself: the 2019 model that was used for this back-casting exercise was fit to data that included peak rates from 4-9pm in addition to 1pm-6pm. Because of this, the model is sensitive to price differentials in the late afternoon and early evening and so predicts larger impacts in those hours relative to the early afternoon historic period. The results reported in the table above are for the historic peak period of 1pm-6pm. The impacts for the September peak day from the 4pm-9pm period is nearly 39%, which is substantially closer to the reported value from PY2018.

5.5 EX POST TO EX ANTE COMPARISON

As shown in Figure 18 the rate updates applied for ex ante were minimal for RTP. The ex ante models were the same as ex post run for each customer under the RTP and OAT tariffs effective January 1, 2020.

Figure 18: Comparison of Ex Post RTP Hourly Generation Rates to Ex Ante



A comparison of ex post and ex ante results are shown in **Table 20**. The difference in ex post and ex ante is attributable to two factors. First, customer churn as customers came on to and left the program changed the mix of response patterns. With a small program like RTP, even small changes in customer counts have a relatively large impact on the overall program results. Second, when modeling ex ante loads, only 2019 load patterns were used to estimate customer load factors, which is relevant for large, standby customers where demand charges contribute a large part of a customer's total bill. A change in an extremely large customer's consumption patterns in 2019 compared to all three years used in ex post also contributes to the increase in impacts in ex ante.

Table 20: Ex Post Compared to 2020 Ex Ante

Weather	Day Type	Enrolled	Average Customer		Temp	Impacts		
			Reference	Observed		kW	%	MW
CAISO 1-in-10	Hot Summer Weekday	101	477.0	269.3	93.0	207.7	43.5	21.0
CAISO 1-in-2	Hot Summer Weekday	101	477.0	269.3	91.1	207.7	43.5	21.0
SCE 1-in-10	Hot Summer Weekday	101	477.0	269.3	93.9	207.7	43.5	21.0
SCE 1-in-2	Hot Summer Weekday	101	477.0	269.3	91.3	207.7	43.5	21.0
Ex Post	Hot Summer Weekday	102	455.7	315.3	87.9	140.3	30.8	14.3

6 DISCUSSION

RTP is a small and successful demand response program that, despite modeling challenges, can provide load reductions during hot summer days for the participants enrolled.

It is clear that RTP customers successfully responded to substantial rate changes that occurred during the 2019 program year. Because of these changes, customers reduced their consumption during the peak period relative to the prior year and exhibited evidence of load shifting between the on peak and off-peak periods. The majority of load impacts from this program come from large customers for whom price response can have a significant impact on their bills

The RTP program experienced many major changes in 2019 that make comparison to prior years difficult. These changes included

- Substantial customer churn in the fall of 2018 and spring of 2019
- Change in ex ante weather conditions
- New TOU rate blocks for both RTP and otherwise applicable tariffs
- Narrower peak period RTP pricing
- Consolidation of RTP summer weekday day types from five to three

As a result, considerable changes to the ex post and ex ante results were not unexpected. Nevertheless, the program continues to deliver peak period reductions of approximately 30% on Hot Summer Weekdays. Factoring in customer churn, updated consumption patterns, and updated rates for ex ante forecasts, customers can experience nearly 47% impacts during the RA window on Hot Summer Days going forward.

Of considerable interest for subsequent years will be customer response over time as customers become acquainted with the new price schedules. Since the new rates went into effect between March 1 2019 and June 1 2019, they have only experienced between five and six months of the new tariffs as of this evaluation. With more time on the new rates, their response patterns may change and reflect their ability to reduce loads in the 4pm-9pm window more consistently.

7 APPENDIX: EVALUATION METHODOLOGY

Demand Response Evaluation Methods

The primary challenge of impact evaluation is the need to accurately detect changes in energy consumption while systematically eliminating plausible alternative explanations for those changes, including random chance. Did the dispatch of demand response resources cause a decrease in hourly demand? Or can the differences be explained by other factors? To estimate demand reductions, it is necessary to estimate what demand patterns would have been in the absence of dispatch – this is called the counterfactual or reference load. At a fundamental level, the ability to measure demand reductions accurately depends on four key components:

- The effect or signal size – The effect size is most easily understood as the percent change. It is easier to detect large changes than it is to detect small ones. For most DR programs, the percentage change in demand is relatively large.
- Inherent data volatility or background noise – The more volatile the load, the more difficult it is to detect small changes. Energy use patterns of homes with air conditioners tend to be more predictable than industrial or agricultural load patterns.
- The ability to filter out noise or control for volatility – At a fundamental level, statistical models, baseline techniques, and control groups – no matter how simple or complex – are tools to filter out noise (or explain variation) and allow the effect or impact to be more easily detected.
- Sample/population size – For most of the programs in question, sample sizes are irrelevant because we analyzed data for the full population of participants either using AMI data or thermostat runtime. Sample size considerations aside, it is easier to precisely estimate average impacts for a large population than for a small population because individual customer behavior patterns smooth out and offset across large populations.

In general, there are seven main methods for estimating demand reductions, as summarized in Table 21. The first four only make use of use patterns during days when DR is not dispatched to calculate the baseline. The latter three methods incorporate non-event data but also use an external control group to establish the baseline. The control group consists of customers who are similar to participants, experienced the same event day conditions, but are not dispatched during events (or were not transitioned to time-varying pricing). Control and participant groups should have similar energy usage patterns when the intervention is not in place and diverge when the intervention is in effect. The only systematic difference between the two groups should be that one is dispatched for events (or transitioned to time-varying prices) while the other group is not.

Table 21: Methods for Demand Response Evaluation

General Approach		Method	Method Description
Use non-event days only to establish the baseline	1	Day matching baseline	This approach relies on electricity use in the days leading up to the event to establish the baseline. A subset of non-event days in close proximity to the event day are identified (e.g., Top 3 of 10 prior days). The electricity use in each hour of the identified days is averaged to produce a baseline. Day matching baselines are often supplemented with corrections to calibrate the baseline to usage patterns in the hours preceding an event – usually referred to as in-day or same-day adjustments.
	2	Weather matching baseline	The process for weather matching baselines is similar to day-matching except that the baseline load profile is selected from non-event days with similar temperature conditions and then calibrated with an in-day adjustment.
	3	Regression models (interrupted time series)	Regression models quantify how different observable factors such as weather, hour of day, day of week, and location influence energy use patterns. Regression models can be informed by electricity use patterns in the day prior (day lags) and in the hours before or after an event (lags or leads) and can replicate many of the elements of day and weather matching baselines.
	4	Machine learning (w/o external controls)	Most machine learning approaches (e.g., random forest, neural networks, etc.) rely exclusively on non-event day data to establish the baselines. The algorithms test different model specifications and rely on a training and testing datasets (out-of-sample testing) to identify the best model and avoid overfitting.
Use non-event days plus a control group to establish the baseline	5	Matched control groups	Matching is a method used to create a control group out of a pool of nonparticipant customers. This approach relies on choosing customers who have very similar energy use patterns on non-event days and a similar demographic and geographic footprint. The non-event day data is incorporated by either analyzing the data using a regression model, a difference-in-differences model, or both.
	6	Synthetic control groups	This approach is similar to matching except that multiple controls are used and weighted according to their predictive power during a training period. A key advantage of this approach is that it can be used to produce results for individual customers.
	7	Randomized control trials	Participants are randomly assigned to different groups, and one group (the "control" group) is withheld from dispatch to establish the baseline. The control group provides information about what electricity use would have been in the absence of DR dispatch – the baseline. The estimate is refined by netting out any differences between the two groups on hot non-event days (difference-in-differences).

Approaches that use an external control group typically provide more accurate and precise results on an aggregate level when there are many customers (i.e., several hundred). They also make use of non-event days to establish the baseline but have the advantage of also being informed by the behavior of the external control group during both event and non-event days. Except for synthetic controls, the two fundamental limitations to control groups have been: the limited ability to disaggregate results, and the inability to use control groups for large, unique customers. The precision of results for control group methods rapidly decrease when results are disaggregated, and a control group cannot be used to estimate outcomes for individual customers (except for synthetic controls).

Methods that rely only on non-event days to establish the baseline – such as individual customer regressions – are typically more useful for more granular segmentation. Individual customer regressions have the benefit of easily producing impact estimates for any number of customer segments. Because they are aggregated from the bottom up, the results from segments add up to the totals. However, the success of individual customer regression hinges on having non-event days comparable to event days. When most of the hottest days are event days, as has been the case historically, estimating the counterfactual requires extrapolating trends to temperature ranges that were not experienced during non-event days. This produces less accurate and less reliable demand reduction estimates for the hottest days when resources are needed most.

Model Selection

A key question every evaluator must address is how to decide which model produces the most accurate and precise counterfactual. In many instances, multiple counterfactuals are plausible but provide different estimated demand reductions. Model selection plays a role both in developing matching models and for individual customer regressions.

Our process for model selection relies on splitting the data into testing and training days and implementing an out-of-sample testing process. First, we define testing and training days. Days with actual events are not included in either the training or testing days. Next, ten or more model specifications are defined. Because the treatment is not activated during either the training or testing days, the impacts are by definition zero. Any estimated impact by models is in fact due to model error. Third, we run each of the models using the training data and predict out-of-sample loads for the testing days. Fourth, the testing data out-of-sample predictions are compared to actual electricity use and used to calculate metrics for bias and fit. Next, the best model is identified by first narrowing the candidate models to the three with least bias (or with % bias less than 1%) and then selecting the model with the best fit. Finally, the best performing model is applied to all days and used to estimate the counterfactual for actual event days. The final model is designed to produce load impacts (treatment effects) for each event day and hour. Figure 19 illustrates the process.

Figure 19: Model Selection and Validation

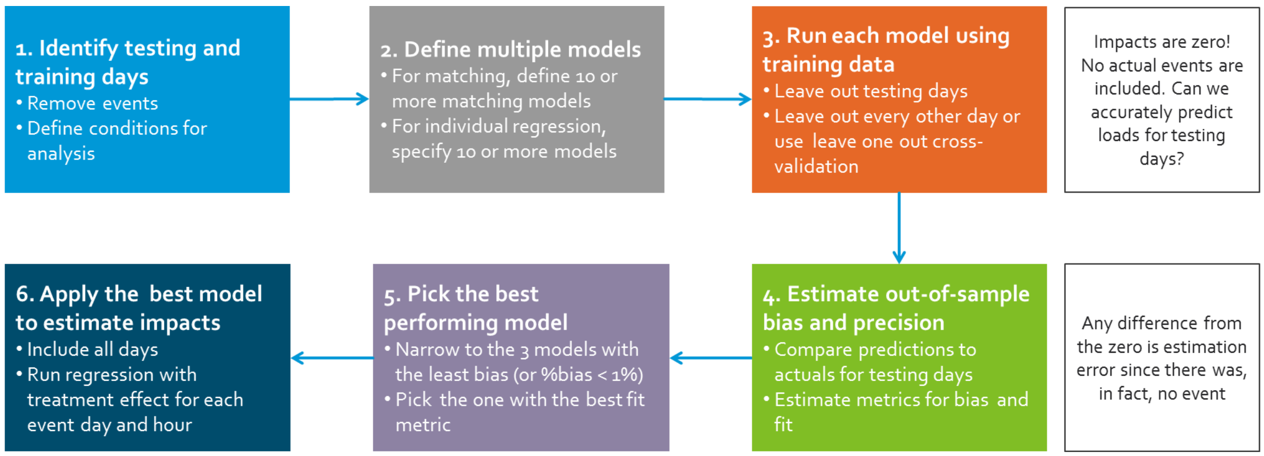


Table 22 summarizes the metrics for bias and precision we employ. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error describes the relative magnitude and direction of the bias. A negative value indicates a tendency to under predict, and a positive value indicates a tendency to over predict. This tendency is best measured using multiple days and hours. 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 is used to narrow down to the three models with the least bias. The Relative RMSE metric is used to identify the most precise and final model among the remaining candidates.

Table 22: Definition of Bias and Precision Metrics

Type of Metric	Metric	Description	Mathematical Expression
Bias	Average Error	Absolute error, on average	$AE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$
	% Bias	Indicates the percentage by which the measurement, on average, over or underestimates the true demand reduction.	$\%\ Bias = \frac{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)}{\bar{y}}$
Precision	Root mean squared error (RMSE)	Measures how close the results are to the actual answer in absolute terms, penalizes large errors more heavily	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$
	Relative 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 23 and **Table 24** show the out of sample testing results overall for all models tested and by rate family for the selected model. The process to pick the best model overall relied on a combination of visual and statistical tests to identify the best model. As a first pass, some models included weather variables, which generally improved performance. However, the risk of introducing confounding variables in to an evaluation where the treatment (prices) is dependent upon weather was deemed too great. As a result, models 0, 2, 3 and 7 were immediately excluded from consideration as they included weather variables. Of the remaining models, results were scrutinized for fit across all customers, with special attention paid to the fit on large customers. As a result, Model 4 was chosen as it did not include weather variables, performed well across all customers, and did not fail any visual checks or show poor results for key customer segments.

Table 23: Best Model Out of Sample Fit by Rate Family

Model	Rate	Observed Usage	Avg Error	% Bias	cvRMSE
4	Standby: TOU-8-S	XXX	XXX	XXX	XXX
4	Standby: TOU-GS1	XXX	XXX	XXX	XXX
4	TOU-8	742.1	35.0	4.7%	192%
4	TOU-GS1	XXX	XXX	XXX	XXX
4	TOU-GS2	XXX	XXX	XXX	XXX
4	TOU-GS3	XXX	XXX	XXX	XXX
4	TOU-PA-2	XXX	XXX	XXX	XXX
4	TOU-PA-3	XXX	XXX	XXX	XXX

Table 24: All Tested Models Out of Sample Fit

Model	Observed Usage	Avg Error	% Bias	cvRMSE	R-Squared
0	486.2	18.9	3.9%	221%	0.82
1	486.2	17.1	3.5%	223%	0.81
2	486.2	21.3	4.4%	223%	0.81
3	486.2	20.5	4.2%	230%	0.80
4	486.2	19.8	4.1%	225%	0.81
5	486.2	19.5	4.0%	229%	0.80
6	486.2	24.0	4.9%	230%	0.80
7	486.2	-5.7	-1.2%	1344%	0.10
8	486.2	-39.9	-8.2%	223%	0.79