REPORT

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2020 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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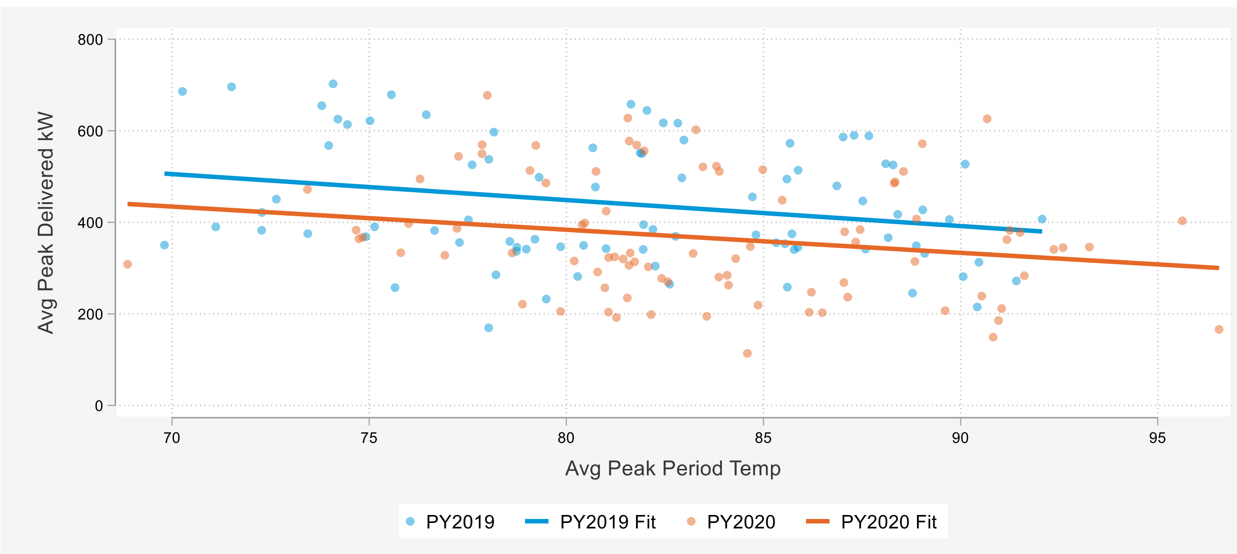
1 EXECUTIVE SUMMARY

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.

A key question to answer in this year's evaluation is to what degree RTP customers were influenced by the economic impacts of the COVID-19 pandemic. Some sectors and industries saw dramatic shifts in energy use and patterns of consumption. RTP customers are mainly large industrial customers who generally saw moderate declines in consumption. This is shown in Figure 1, where peak loads and temperatures in PY2019 and PY2020 are plotted for the same set of customers on summer weekdays. As temperatures increase, loads decline, consistent with the RTP pricing schedule's intention.

Figure 1: Effect of COVID-19 on Temperature-Load Relationship



It is clear from the figure that the participant loads in the summer of 2020 were lower than in the prior year. The relationship between temperature and loads, where temperature is a proxy for the RTP rate schedule that a customer experienced, is consistent from year to year, albeit starting from a lower base in 2020.

RTP enrollments are expected to decline over time, from 105 in 2021 to 93 enrolled customers in 2031. Ex ante impacts are expected to be negligible across the average 4-9pm window (Table 1), however impacts of approximately 9.8MW during the 6pm-9pm hours are observed. Load impacts by hour in the RA window are shown in Table 2. The underlying reason for such large differences between the 4pm - 6pm impacts and the 6pm-9pm impacts has to do with the relative price of the RTP rate compared to the otherwise applicable tariff. Due to the RTP treatment being correlated with weather, 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 from 4pm-9pm

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2021	-0.14	-0.14	-0.14	-0.14
2022	-0.26	-0.26	-0.26	-0.26
2023	-0.30	-0.30	-0.30	-0.30
2024	-0.32	-0.32	-0.32	-0.32
2025	-0.34	-0.34	-0.34	-0.34
2026	-0.34	-0.34	-0.34	-0.34
2027	-0.35	-0.35	-0.35	-0.35
2028	-0.35	-0.35	-0.35	-0.35
2029	-0.35	-0.35	-0.35	-0.35
2030	-0.35	-0.35	-0.35	-0.35
2031	-0.35	-0.35	-0.35	-0.35

Table 2: RTP Aggregate Program Ex Ante Impacts – 2021 August Peak Day by Hour

Hour Ending	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
Avg. 4pm-9pm	-0.14	-0.14	-0.14	-0.14
17	-15.25	-15.25	-15.25	-15.25
18	-14.81	-14.81	-14.81	-14.81
19	6.69	6.69	6.69	6.69
20	14.37	14.37	14.37	14.37
21	8.30	8.30	8.30	8.30

The RTP program can provide a small but measurable amount of demand response impacts during the 6pm-9pm period on Hot Summer Weekdays, when prices relative to the otherwise applicable tariff are high. The program has many customers who are dually enrolled in other demand response programs, making attribution of impacts challenging. Similarly, the program is dominated by several large industrial accounts that provide the majority of the load shed for the program.

As a result, portfolio impacts averaged across the RA window tend to be small. The effects of the COVID-19 pandemic on customers was substantial, and the effect thereof is expected to persist over the 11 years of the forecast horizon.

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 other event-based demand response programs.

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. As a result, PY2020 was the first full year that customers experienced the new rate regime.

There were approximately 110 customers enrolled on RTP rates as of the PY 2020 summer season, up from 102 in last year's evaluation. As this program is rate-based, customer counts tend to fluctuate over time.

2.1 KEY RESEARCH QUESTIONS

The PY2020 evaluation of SCE's RTP program sought to answer these key research questions:

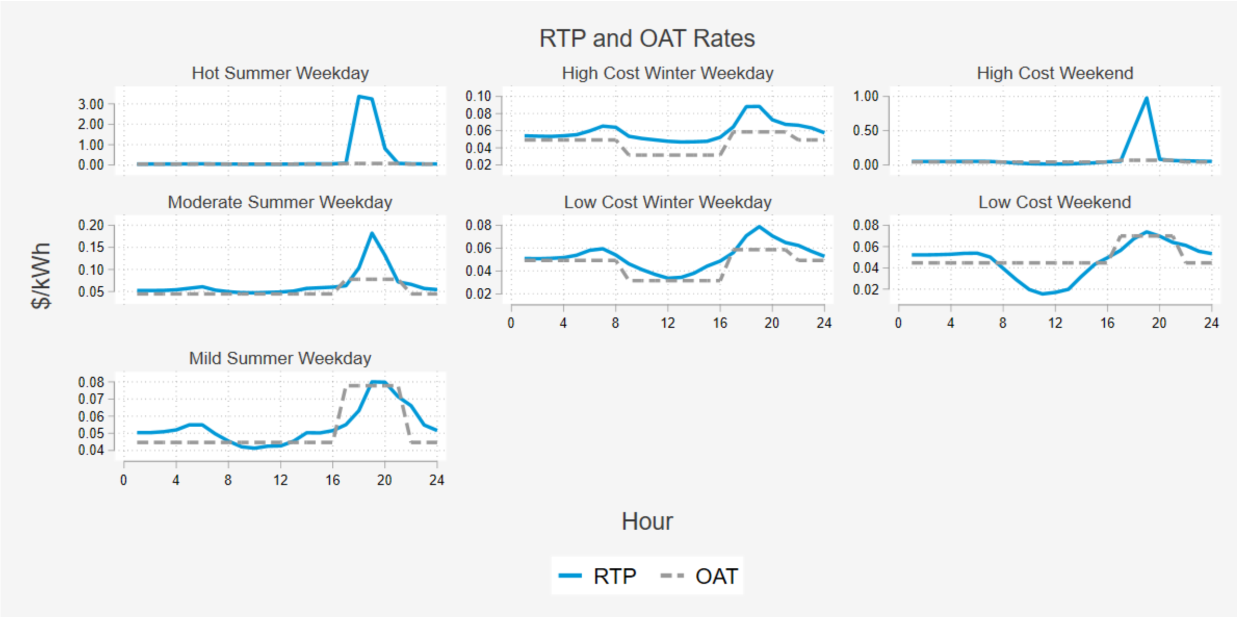
- What were the demand reductions due to program operations and interventions in 2019 – for each RTP day type, monthly average weekday and monthly peak day? How do these results compare to the ex post results from the prior year and why?
- How do load impacts differ for customers who have enabling technology 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 110 customers enrolled in the RTP program, the majority of which are on the TOU-8 rate, SCE's large industrial rate. For simplicity throughout reporting, rates displayed in this report only include TOU-8 details, as most rates are substantively similar.

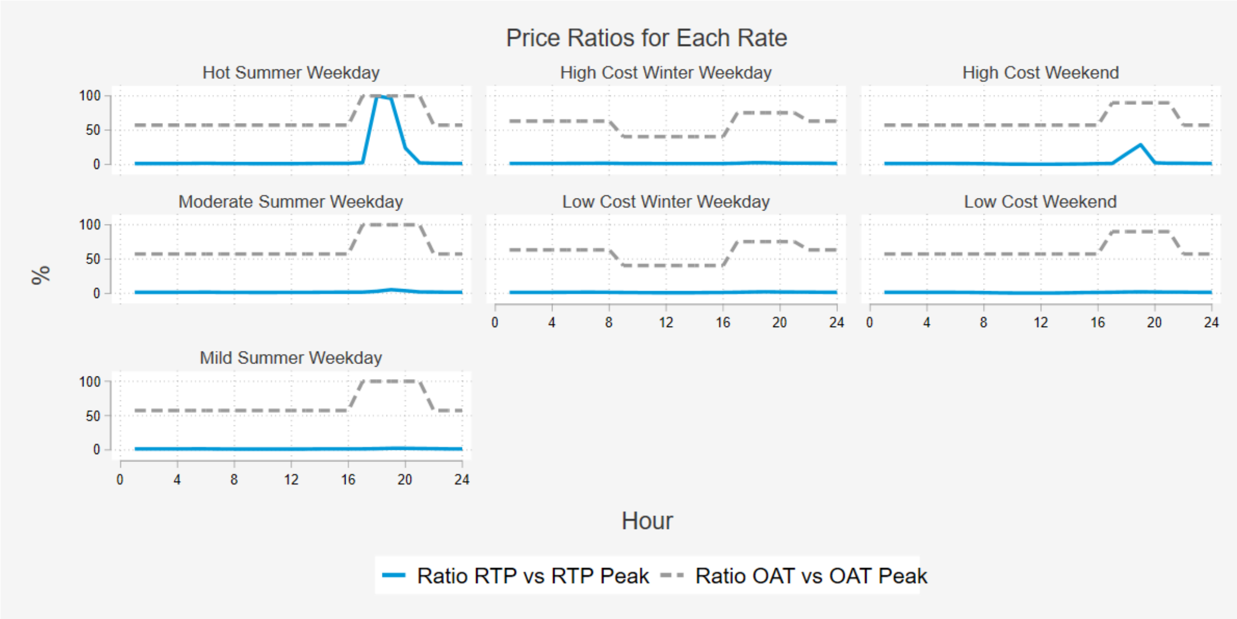
Figure 2 shows the rates experienced by day type for both the TOU-8 RTP and Otherwise Applicable Tariff (OAT), including normalized demand charges. In general, there is minimal difference between the RTP and OAT rates with the exception of Hot Summer Weekdays and High Cost Weekends, where the difference between the two rates can exceed several dollars per kilowatt-hour.

Figure 2: Comparison of RTP and OAT Rates (TOU-8)



While the main goal of this evaluation is to assess the impact of being on the RTP rate compared to the OAT rate, it may also be helpful to assess the impact of the various RTP day types on customer consumption. Figure 3 shows the price ratios associated with each of the two rates, normalized to each rate's maximum value. In both cases, the highest rates that a customer experiences occurs during the 4pm-9pm peak window on hot summer weekdays. However, the RTP peak rate is at its peak between 6-8pm only, a narrower peak than the OAT rate. In addition, the concentration of the price signal in those peak hours stands in contrast with the OAT rate, where in the summer period, peak prices are in place every weekday during the full 4pm-9pm window.

Figure 3: Ratio of Peak to Off-Peak Rates for RTP and OAT (TOU-8)



2.3 PARTICIPANT CHARACTERISTICS

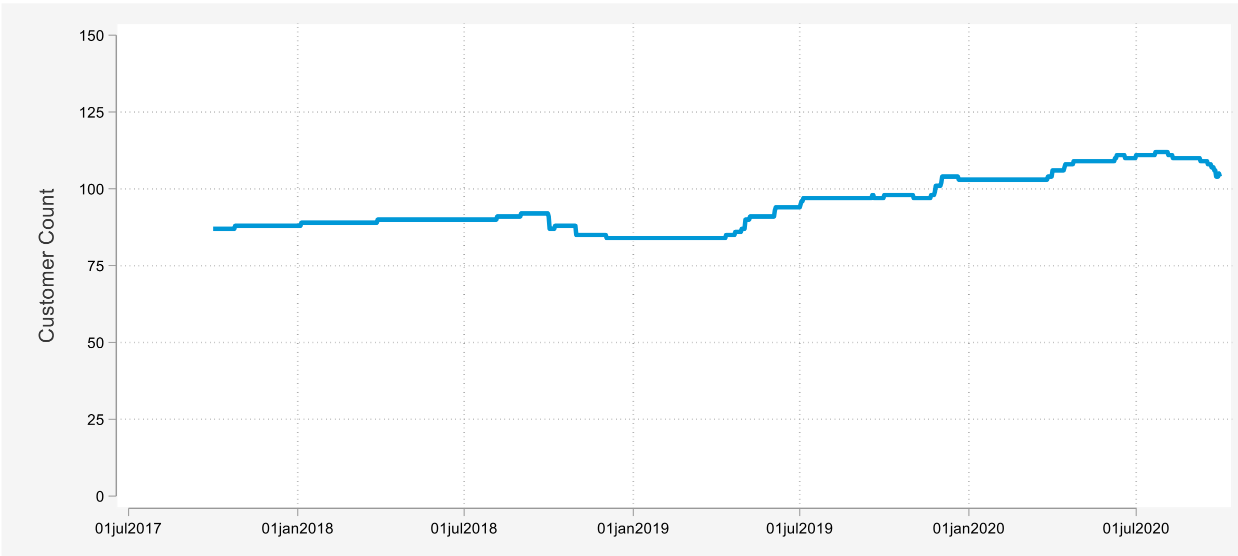
There were 110 commercial, industrial, and agricultural customers active on RTP as of the 2020 peak day, August 18th. Table 3 summarizes their key characteristics. "Manufacturing" was the most common customer industry, with "Wholesale, Transport, Other Utilities and Agriculture, Mining and Construction" 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 – typically TOU-8-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 3: Participant Characteristics on 8/18/2020 Peak Day

Category	Subcategory	Customer Count
Rate Family	TOU-8	66
	TOU-GS1	16
	TOU-GS3	10
	TOU-GS2	7
	TOU-PA-2	6
	TOU-8-S	4
	TOU-PA-3	1
Industry	Manufacturing	36
	Agriculture, Mining, Construction	26
	Wholesale, Transport, Other Utilities	20
	Offices, Hotels, Finance, Services	15
	Unknown/Other	7
	Institutional/Government	4
	Retail Stores	1
	Schools	1
LCA	La Basin	86
	Big Creek/Ventura	18
	Outside LA Basin	6
NEM Type	None	108
	Solar	2
Size	Greater Than 200kW	83
	20kW Or Lower	16
	20-200kW	11
Zone	Remainder Of System	71
	South Of Lugo	27
	South Orange County	12

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. Thereafter, the program generally grew slowly through the summer of 2020.

Figure 4: RTP Enrollment over Time



2.4 2020 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 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 4. PY2020 is the first year for which customers experienced the new rate for the full evaluation period.

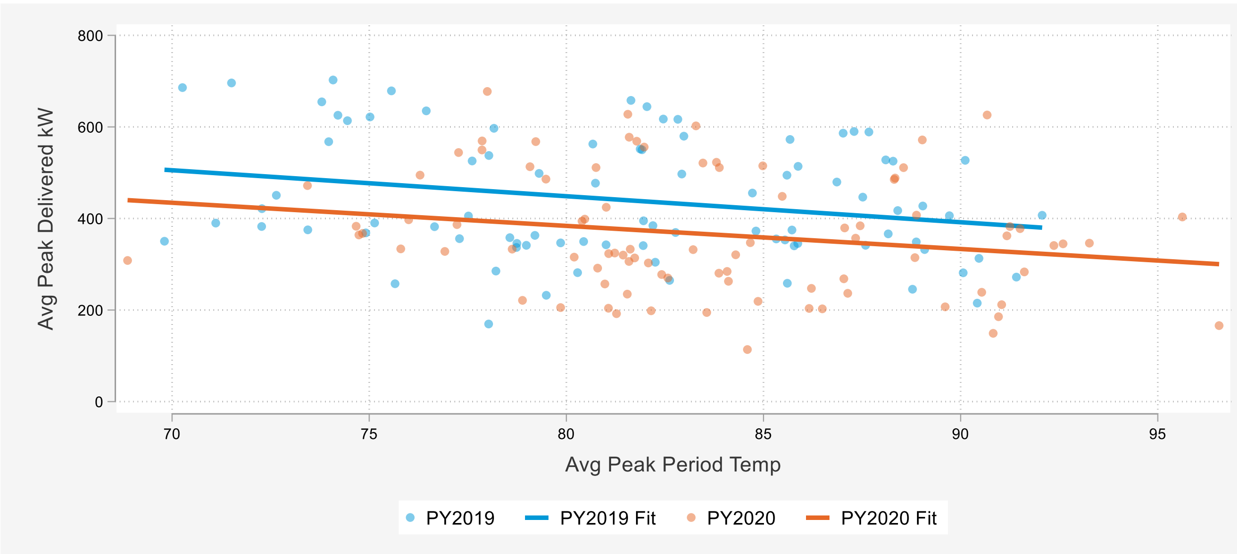
Table 4: Old and New Event Dispatch Criteria

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

2.5 EFFECT OF COVID-19 PANDEMIC ON PARTICIPANT LOADS

A key question to answer in this year's evaluation is to what degree RTP customers were influenced by the economic impacts of the COVID-19 pandemic. Some sectors and industries saw dramatic shifts in energy use and patterns of consumption. RTP customers are mainly large industrial customers who generally saw moderate declines in consumption. This is shown in Figure 5.

Figure 5: Effect of COVID-19 On Temperature-Load Relationship



It is clear from the figure that the participant loads in the summer of 2020 were lower than in the prior year. The relationship between temperature and loads, where temperature is a proxy for the RTP rate schedule that a customer experienced, is consistent from year to year, albeit starting from a lower base in 2020.

2.6 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.

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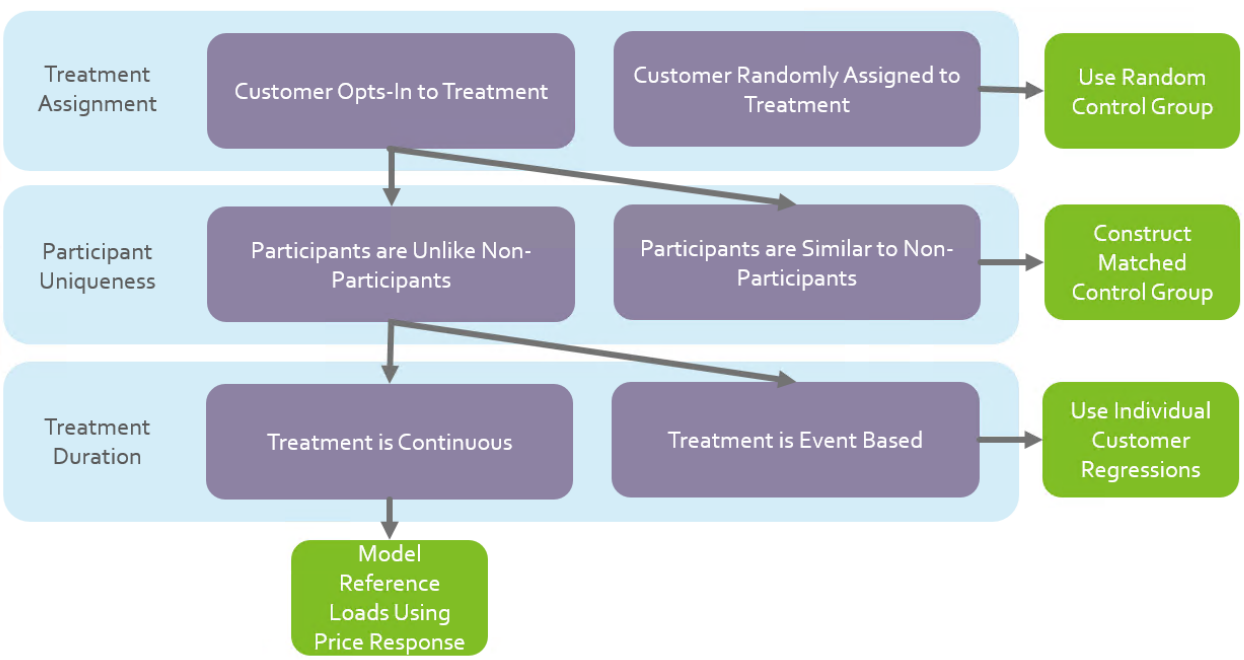
- **Treatment duration:** Once on the rate, customers remain on it. There is no event day comparable to BIP or API.

A summary of the implications of these characteristics is shown in **Figure 6**. 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 6: 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 the evaluation 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 2017-2020 data for participants
3. Use of control groups	Because of the uniqueness of the target population, we relied on a quasi-within-subjects method for developing ex post impacts. Synthetic controls were added to the ex post model for each customer to explain other variation in loads.
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 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.

Methodology Component	Demand Side Analytics Approach
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

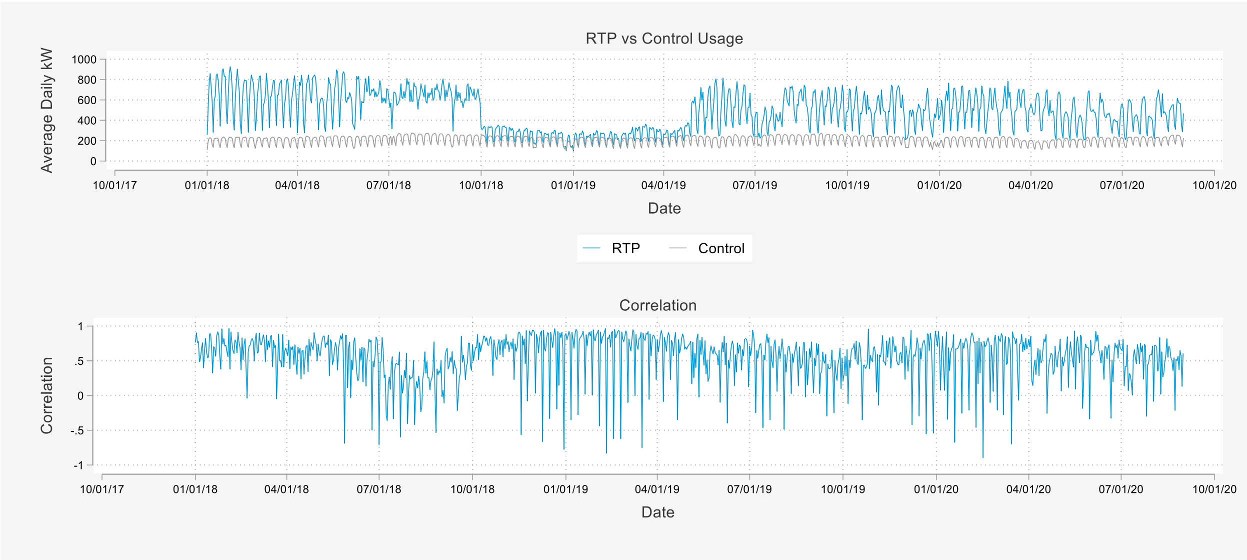
Once each component has been normalized to an hourly per-kWh value, the components for either the RTP or OAT rates are summed.

SYNTHETIC CONTROLS

A key difference in this year's evaluation was the use of synthetic control profiles to improve the accuracy of the ex post impact estimation, particularly in helping to capture the effects of the COVID-19 pandemics' economic effects on industrial customers. Synthetic controls are included in the regression specification as right-hand-side variables and serve as a proxy for other unobserved characteristics that can affect customer loads. To select a synthetic control group for RTP customers, a random subset of customers in the same industries and rate families were sampled in the same proportion as exist in the

RTP population. That is, if 5% of RTP participants are schools with rate family GS-3, 5% of the synthetic control pool also fell in that category. Figure 7 shows how control loads are highly correlated with participant loads. In effect, the control customer profiles, even if they are not the same size as the participants, can explain much of the variation in customer usage on a day-to-day basis, improving the accuracy of the predictions.

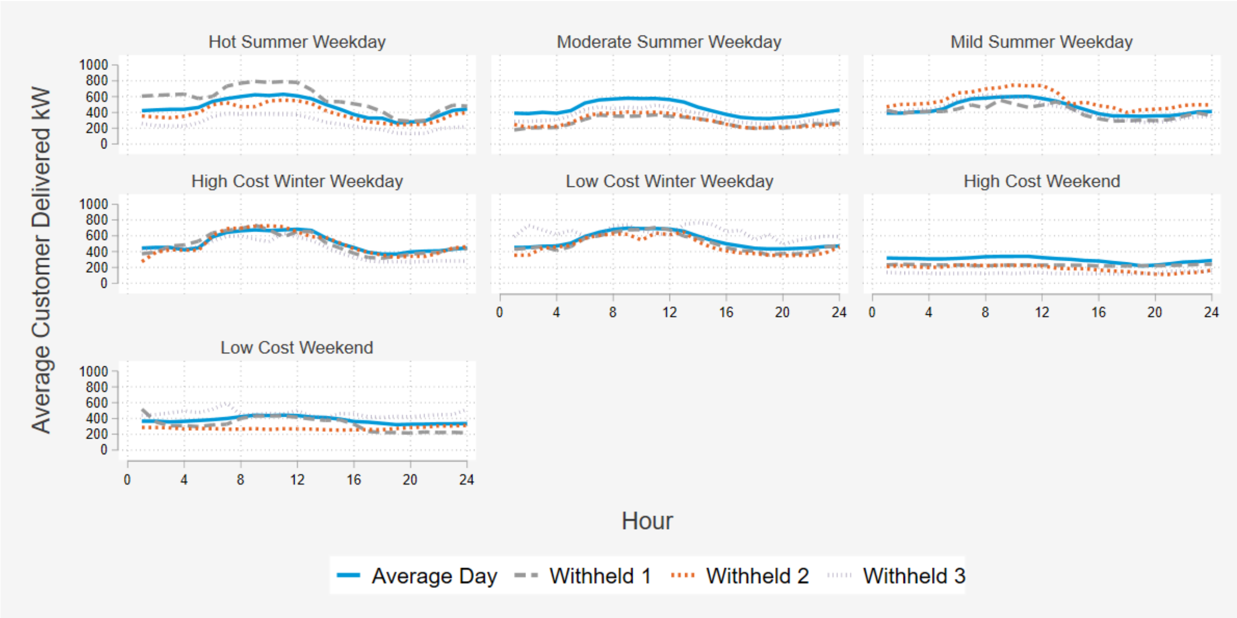
Figure 7: Synthetic Control Variation



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. Three days were selected randomly for each RTP day type, for a total of 21 days. A comparison of the withheld days to the average day for RTP participants is shown in Figure 8.

Figure 8: Comparison of Withheld Days to Average Day



Ex Post Model

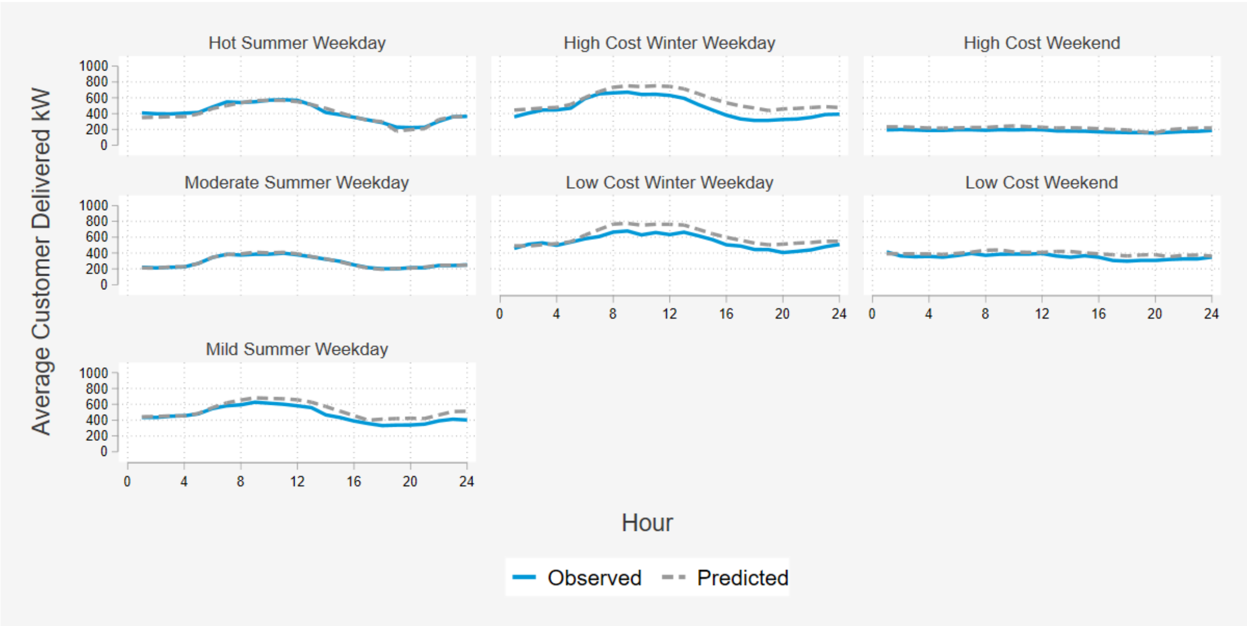
To better account for the effects of COVID-19, fifteen different models were tested, with and without the inclusion of synthetic controls. The framework for tested models, as well as the counts of customers for whom each was their best model, is shown in **Table 8** .

Table 8: Regression Models Tested and Best Model by Customer

		Price & Price Ratio, interacted with Peak/Off Peak Indicators	Price & Price Ratio	Logged Price & Price Ratio	Logged Average Daily Price & Price Ratio	Logged Price	Total by Adjustments
Daytype & Month	No Control	1	1		2	4	8
	All RTP-Like Customers	3	1	1	3	1	9
	Profiles by Industry	2	1	2	3	8	16
	Profiles by Rate	2	1		1	5	9
Day of Week & Month	No Control	1		1			2
	All RTP-Like Customers	2		2	1	4	9
	Profiles by Industry	1	2		2	1	6
	Profiles by Rate	1		1	1		3
Day of Week, COVID Indicator, & Month	No Control	1	1		3	1	6
	All RTP-Like Customers	4	3	3		9	19
	Profiles by Industry	6		3	3	2	14
	Profiles by Rate	1	3	3	1	5	13
Total by Price Model		25	13	16	20	40	114

As discussed at the end of Section 2.6, 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 9 shows the predicted loads for each withheld day type. More detail, including a summary of model fit statistics, can be found in the appendix.

Figure 9: Out of Sample Predictions on Withheld Days



Because modeling was performed on an individual customer basis, the specification for each customer will vary slightly. However, the structure of each customer's regressions were similar: running a separate model for each customer and each hour with the following components.

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

Equation 1: Ex Post Regression

$$kW_{ih} = \alpha_{0h} + (price(s)) + (month\,\&\,day\ of\ week) + (synthetic\ control) + \varepsilon_{ih}$$

Table 9: Regression Models Tested and Best Model by Customer

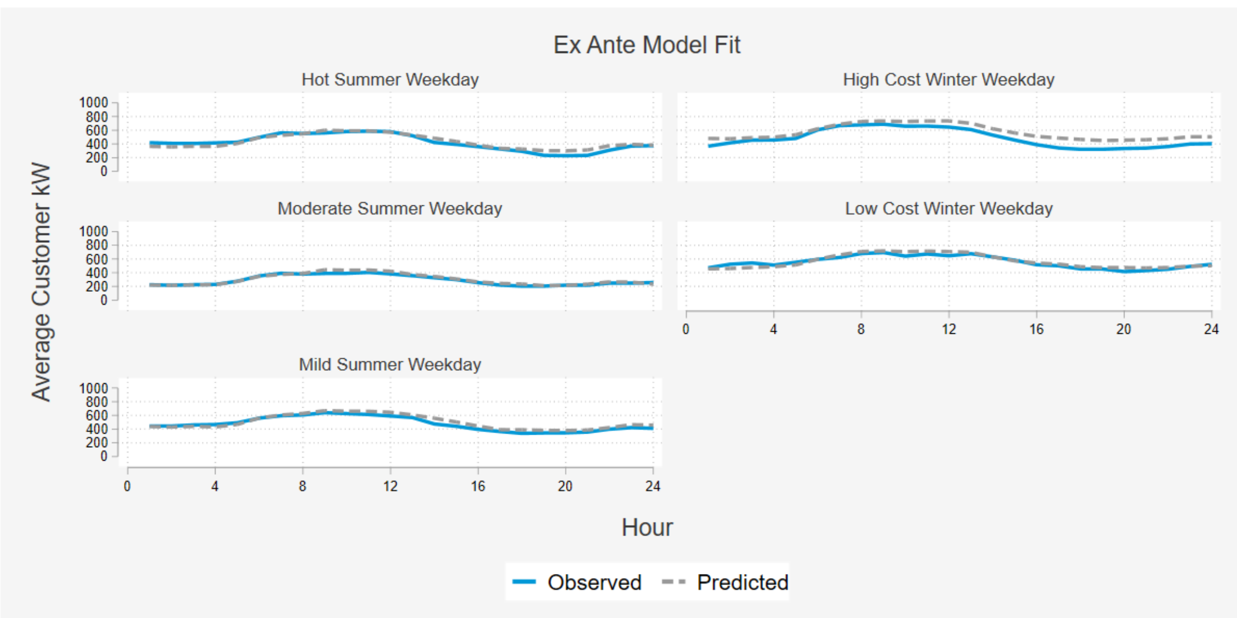
Category	Model Term	Description
Base	kW_{ih}	Electricity delivered in kW for customer i, in hour h
	α_{0h}	Intercept
	ε_{ih}	Error term
Price	price	Hourly energy price inclusive of demand charges
	proxy-peak	Indicator variable for on peak hours
	price squared	Square of hourly energy price
	price ratio	Ratio of hourly price to the daily max price
	proxy-offpeak	Indicator variable for off peak hours
	lnprice	Natural log of hourly price
	lnpriceratio	Natural log of the price ratio
	lndailyaverageprice	Natural log of the daily average price
Month/Day of Week	daytype	Day of week indicators grouping Monday, Tuesday-Thursday, Friday, and Weekends/Holidays
	Month	Month indicator variable
	dow	Day of week indicator variables
	covid	Indicator for post-COVID period (March 2020 onward)
Synthetic Control	ctrl_kwh_all	Profile of average RTP-like control customer
	ctrl_kwh_ind_*	Profiles for average RTP-like control customers by industry
	ctrl_kwh_rate_*	Profiles for average RTP-like control customers by rate

Ex Ante Reference Load Model

The reference load modeling approach for ex ante was identical to that of ex post, with the notable exclusion of synthetic control profiles, as these do not have an ex ante equivalent data stream. 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. The results of the ex ante out of sample testing analysis are summarized in Figure 10.

Figure 10: Model Out of Sample Fit based on Data Used



An important adjustment in the ex ante modeling in PY2020 was the inclusion of a forecast of the effects of COVID-19 over the forecast horizon. In discussion with SCE, a glide path was developed

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

based on expected adjustments to the sales forecast for each sector, and that adjustment was added to the ex ante model. **Table 10** shows the results of this glide path for the industrial sector. A value of 100% indicates the effect of COVID-19 on participants loads will be the same as in 2020, while a value of 50% indicates that 50% of the load changes associated with the pandemic will persist, with 50% rebounding to the pre-pandemic levels. A value of 0% indicates that loads will have rebounded to pre-pandemic levels altogether.

Table 10: Forecasted Index of COVID-19 Effects

2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
100.00%	50.00%	25.00%	12.50%	6.25%	3.13%	1.56%	0.78%	0.39%	0.20%	0.10%	0.00%

3.2 ALTERNATE SPECIFICATION TESTED

The SCE evaluation and program staff were interested in testing an alternate specification for this year's evaluation in conjunction with the standard price models. In this version, the higher price RTP day types would be treated as an event, and their impacts modeled with an event indicator and without price signals. This model would essentially treat Mild Summer Weekdays, Low Cost Winter Weekdays, and Low Cost Weekends as the baseline performance of these customers, with impacts set to zero. Any deviation from these base profiles on Moderate Summer Weekdays, Hot Summer Weekdays, High Cost Winter Weekdays and High Cost Weekends would be impacts associated with the program.

This approach does not measure the impact of being on an RTP rate compared to the OAT rate. Instead, it measures the amount of load shed associated with the high price RTP day types, relative to the low price RTP day types.

In this approach, three distinct periods are modeled: summer weekdays, winter weekdays, and weekends. An indicator variable is added to the model to reflect each event day for each periods and the coefficient $\beta_{e,i,h}$on the event day is the impact of the pricing schedule on participant loads.

Equation 2: Alternate Ex Post Regression

$$kW_{ih} = \alpha_{0h} + \sum_{e=0}^{2} \beta_{e,i,h} * event_{e,i,h} + (synthetic\ control) + \varepsilon_{ih}$$

Table 11: Alternate Specification Event Categories

	Base (Event = 0)	Event 1	Event 2
Summer Weekdays	Mild Summer	Moderate Summer	Hot Summer
Winter Weekdays	Low Cost	High Cost	
Weekends	Low Cost	High Cost	

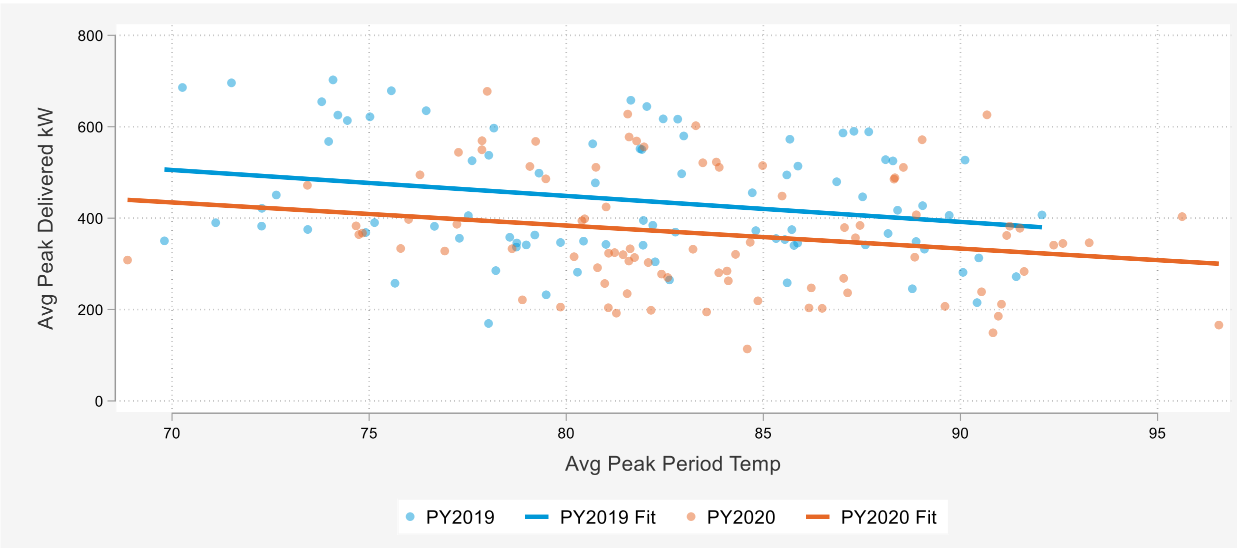
4 EX POST RESULTS

This section details the results of the ex post analysis, with particular attention paid to the impact of the COVID-19 pandemic, the program's performance on the extreme heat waves in August and September, and the general impact of RTP prices on customer loads.

Consumption Changes Associated with COVID-19

A key question to answer in this year's evaluation is to what degree RTP customers were influenced by the economic impacts of the COVID-19 pandemic. Some sectors and industries saw dramatic shifts in energy use and patterns of consumption. RTP customers are mainly large industrial customers who generally saw moderate declines in consumption. This is shown in Figure 11.

Figure 11: Effect of COVID-19 on Temperature-Load Relationship



It is clear from the figure that the participant loads in the summer of 2020 were lower than in the prior year. The relationship between temperature and loads, where temperature is a proxy for the RTP rate schedule that a customer experienced, is consistent from year to year, albeit starting from a lower base in 2020.

RTP Performance During Extreme Conditions

Separately, extreme weather conditions in August and September of 2020 were associated with many coincident calls for demand response of all forms to mitigate capacity constraints. Due to the nature of how the RTP rate is dispatched, RTP customers did not generate substantial amounts of demand response on these days. The RTP rate dispatched for each day is listed in **Table 12** for the two extreme weeks of weather. In the majority of cases, customers were not exposed to the most extreme RTP rate signal and therefore were not shedding large amounts of load.

Table 12: RTP Day Types on Key Dates

August	September
14th – Medium Summer Weekday*	5th – High Cost Weekend
15th – High Cost Weekend*	6th – High Cost Weekend
16th – High Cost Weekend	7th – Hot Summer Weekday
17th – Hot Summer Weekday	
18th – Medium Summer Weekday**	

** Days when SCE was directed to initiate rolling outages per CAISO*

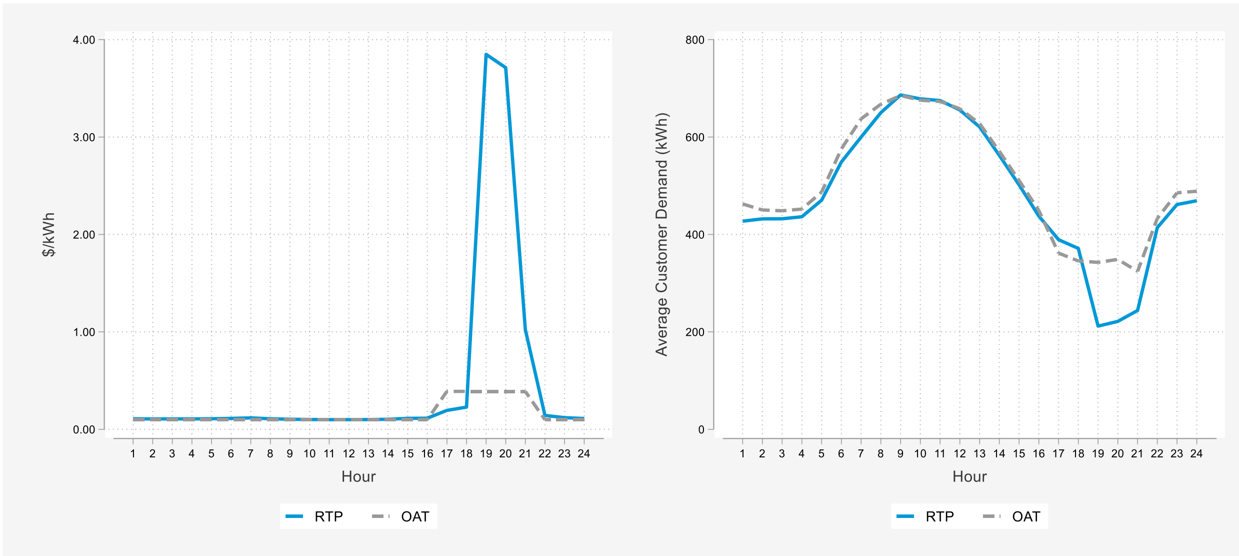
*** SCE System Peak Day*

Coincident to these extreme periods but unrelated to them, one large RTP customer's metering equipment went offline starting on August 14th, 2020 and remained nonfunctional through mid-September. This customer has historically provided substantial load reductions during periods of peak demand, however their impacts during this period are not known as a result of lack of metering.

Measuring RTP Impacts During the Peak Window

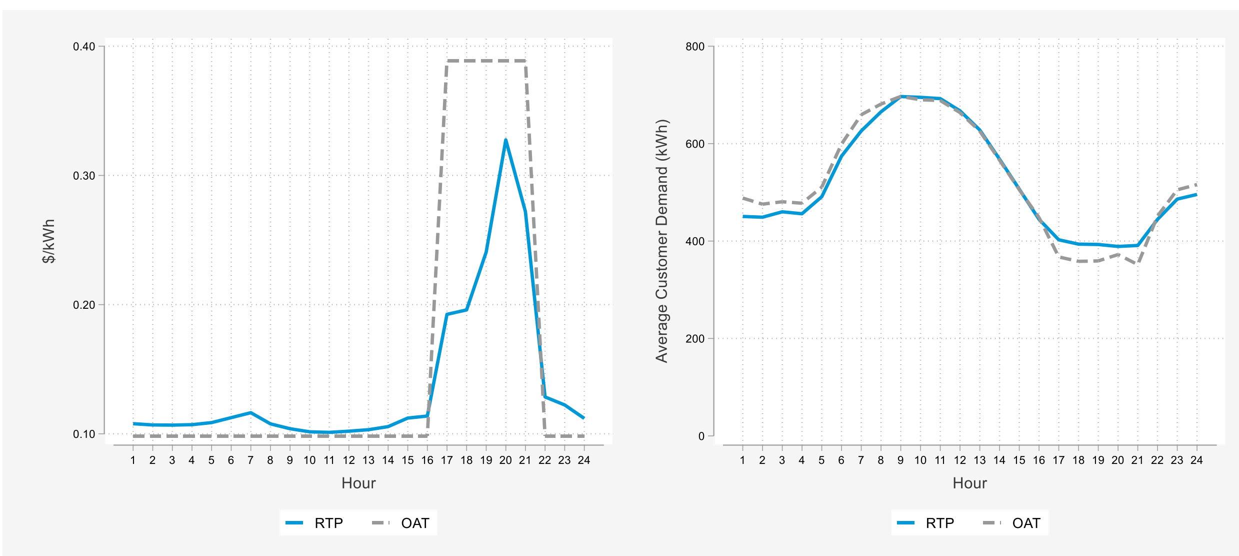
The RTP rate is designed to produce load reductions during key hours on hot days. This targeted approach is shown in the RTP rates overall, where customers experience high rates between 6-9pm on hot summer weekdays, and relatively discounted rates in all other hours. However, the otherwise applicable tariffs for these customers would expose them to relatively higher rates in the 4pm-6pm window therefore resulting in relatively higher loads for RTP customers in this period, as shown in Figure 12. Reporting for the program impacts is averaged across the full peak hours, from 4pm to 9pm. As a result, the load impacts from the RTP program's Hot Summer Weekdays are diluted by this relative increase.

Figure 12: OAT Peak Hours vs RTP Peak Hours on the Average Hot Summer Weekday



The same graph for Moderate Summer Weekdays is below. In the peak hours, the overall OAT rate is higher than the RTP rate, leading to relatively higher loads for RTP customers and load impacts that are negative for the RTP program.

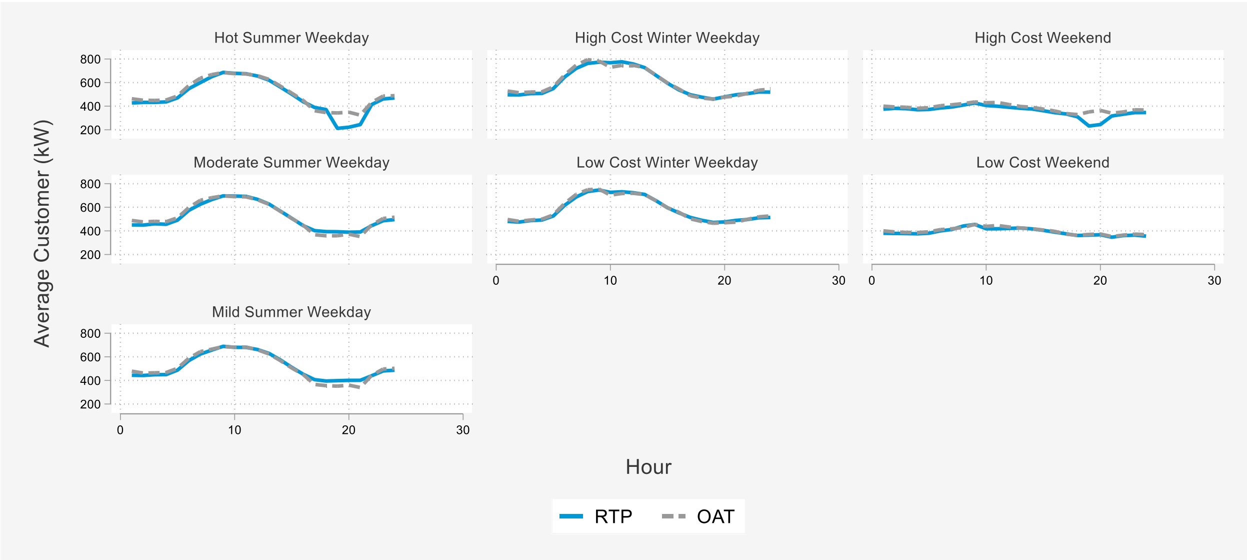
Figure 13: OAT Peak Hours vs RTP Peak Hours on the Average Moderate Summer Weekday



4.1 OVERALL RESULTS

As discussed above, the 2020 SCE system peak day was classified as an RTP Moderate Summer Weekday, and customers were not exposed to a significant price differential relative to their otherwise applicable tariff. On this day, customers increased their usage during the 4pm-9pm window by 0.6MW, or 3.2%. This increase in usage was not statistically significant. The average ex post impacts by RTP day type are shown in Figure 14. As shown, most day types experience essentially no impacts while Hot Summer Weekdays and High Cost Weekends show a load reduction during peak hours. And as mentioned above, when OAT prices are higher than RTP prices, load increases relative to the otherwise applicable tariff can occur. 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.

Figure 14: Average Ex Post Impacts by RTP Day Type



On the following pages, load profiles for the August 18th System Peak Day are shown. Despite being the system peak day, the day is classified as a Moderate Summer Weekday based on the temperature forecast for Downtown Los Angeles. As a result, load impacts across the day are minimal as customers are not exposed to the highest RTP prices. **Table 13** shows the ex post results by month and day type. The June Average Weekday and Monthly Peak Days in PY2020 were classified as Hot Summer Weekdays. On those days, the program delivered an average of approximately a 15% decrease in loads during the peak period, equivalent to 6.24-6.32MW of load reduction.

Table 13: Ex Post Impacts by Day Type for All Customers

Day Type	# Cust	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
January - Average Weekday: Low Cost Winter Weekday	103	539.46	548.96	-9.50	-179.65	-1.8	-0.98
January - Monthly Peak Day: Low Cost Winter Weekday	103	535.12	544.62	-9.50	-189.71	-1.8	-0.98
February - Average Weekday: Low Cost Winter Weekday	103	517.05	527.32	-10.27	-158.56	-2.0	-1.06
February - Monthly Peak Day: Low Cost Winter Weekday	103	512.30	522.57	-10.27	-159.81	-2.0	-1.06
March - Average Weekday: Low Cost Winter Weekday	103	532.94	543.42	-10.48	-220.11	-2.0	-1.08
March - Monthly Peak Day: Low Cost Winter Weekday	103	536.34	545.85	-9.50	-252.77	-1.8	-0.98
April - Average Weekday: Low Cost Winter Weekday	108	470.60	480.13	-9.53	-201.52	-2.0	-1.03
April - Monthly Peak Day: High Cost Winter Weekday	109	462.15	467.80	-5.65	-220.54	-1.2	-0.62
May - Average Weekday: Low Cost Winter Weekday	109	389.14	398.19	-9.05	-187.77	-2.3	-0.99
May - Monthly Peak Day: Low Cost Winter Weekday	109	444.77	453.83	-9.05	-206.02	-2.0	-0.99
June - Average Weekday: Hot Summer Weekday	109	379.53	321.54	57.99	-195.72	15.3	6.32
June - Monthly Peak Day: Hot Summer Weekday	111	377.77	321.52	56.25	-188.12	14.9	6.24
July - Average Weekday: Mild Summer Weekday	112	347.27	392.17	-44.90	-190.87	-12.9	-5.03
July - Monthly Peak Day: Moderate Summer Weekday	112	336.54	368.16	-31.62	-183.26	-9.4	-3.54
August - Average Weekday: Moderate Summer Weekday	110	416.26	449.69	-33.43	-204.04	-8.0	-3.68
August - Monthly Peak Day: Moderate Summer Weekday	109	164.12	169.45	-5.33	-306.67	-3.2	-0.58
September - Average Weekday: Moderate Summer Weekday	108	205.40	210.65	-5.26	-168.69	-2.6	-0.57
September - Monthly Peak Day: Moderate Summer Weekday	103	209.55	214.92	-5.37	-178.46	-2.6	-0.55
October - Average Weekday: Low Cost Winter Weekday	98	484.44	494.72	-10.28	-143.44	-2.1	-1.01
October - Monthly Peak Day: High Cost Winter Weekday	98	489.06	495.07	-6.01	-146.47	-1.2	-0.59
November - Average Weekday: Low Cost Winter Weekday	97	508.76	519.31	-10.55	-181.06	-2.1	-1.02
November - Monthly Peak Day: High Cost Winter Weekday	97	443.20	449.83	-6.62	-149.97	-1.5	-0.64
December - Average Weekday: Low Cost Winter Weekday	104	457.79	467.28	-9.49	-164.26	-2.1	-0.99
December - Monthly Peak Day: Low Cost Winter Weekday	104	459.79	469.28	-9.49	-155.74	-2.1	-0.99

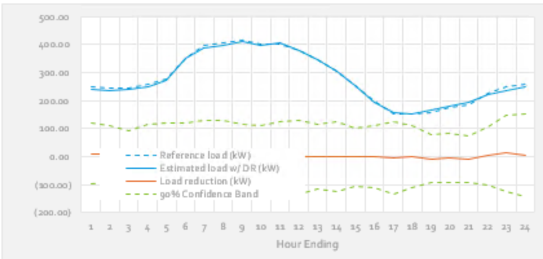
Figure 15: Average Customer Ex Post Impacts on August 18, 2020

Table 1: Menu options

Program	RTP
Reporting Level	Average Customer
Customer Segment	All
Subcategory	All Customers
Ex Post Daytype	Monthly Peak Day
Month	August

Table 2: Event day information

Total sites	109
Daily maximum temperature	101.2
Peak Period (4pm-9pm) Impact (kW)	-5.3
Peak Period (4pm-9pm) Impact (%)	-3.2%
Date	August 18, 2020
RTP Daytype	Moderate Summer Weekday



Hour ending	Reference load (kW)	Estimated load w/ DR (kW)	Load reduction (kW)	% Load reduct	Avg temp (F, site	Uncertainty adjusted impact - Percentiles 5th	10th	30th	50th	70th	90th	95th	Std. error	T-statistic
1	248.91	238.94	9.96	4%	79.23	(129.81)	(98.94)	(34.60)	9.96	54.53	118.87	149.74	84.98	0.12
2	243.08	233.68	9.40	4%	78.24	(118.56)	(90.30)	(31.40)	9.40	50.19	109.10	137.36	77.79	0.12
3	246.98	242.16	4.82	2%	77.52	(108.71)	(83.63)	(31.37)	4.82	41.02	93.28	118.35	69.02	0.07
4	256.44	248.94	7.50	3%	76.69	(128.87)	(98.75)	(35.97)	7.50	50.98	113.76	143.88	82.91	0.09
5	276.05	272.16	3.88	1%	75.65	(143.43)	(110.89)	(43.08)	3.88	50.85	118.66	151.20	89.56	0.04
6	351.40	352.40	(0.99)	0%	75.00	(157.06)	(122.59)	(50.75)	(0.99)	48.77	120.61	155.08	94.89	(0.01)
7	395.84	389.28	6.56	2%	74.73	(149.59)	(115.11)	(43.23)	6.56	56.34	128.22	162.71	94.93	0.07
8	405.16	398.44	6.71	2%	74.50	(149.15)	(114.72)	(42.98)	6.71	56.40	128.15	162.57	94.76	0.07
9	415.73	410.75	4.99	1%	74.49	(138.14)	(106.53)	(40.65)	4.99	50.62	116.50	148.11	87.02	0.06
10	399.91	399.28	0.64	0%	76.19	(143.45)	(111.62)	(45.30)	0.64	46.57	112.90	144.72	87.60	0.01
11	404.10	404.52	(0.42)	0%	80.60	(158.49)	(123.58)	(50.82)	(0.42)	49.97	122.73	157.64	96.10	(0.00)
12	380.15	381.06	(0.91)	0%	86.18	(170.70)	(133.20)	(55.04)	(0.91)	53.22	131.38	168.88	103.22	(0.01)
13	344.72	344.96	(0.24)	0%	90.89	(150.42)	(117.25)	(48.12)	(0.24)	47.64	116.77	149.94	91.30	(0.00)
14	303.22	303.86	(0.64)	0%	94.48	(160.02)	(124.82)	(51.45)	(0.64)	50.17	123.54	158.74	96.90	(0.01)
15	254.82	255.29	(0.47)	0%	98.55	(134.31)	(104.75)	(43.14)	(0.47)	42.20	103.81	133.37	81.37	(0.01)
16	197.09	195.65	1.44	1%	100.06	(141.22)	(109.71)	(44.04)	1.44	46.93	112.60	144.11	86.73	0.02
17	151.70	155.70	(3.99)	-3%	101.16	(170.48)	(133.71)	(57.07)	(3.99)	49.08	125.72	162.49	101.22	(0.04)
18	153.80	153.98	(0.18)	0%	97.47	(139.65)	(108.84)	(44.64)	(0.18)	44.29	108.49	139.29	84.79	(0.00)
19	156.45	163.98	(7.53)	-5%	93.49	(115.56)	(91.70)	(41.97)	(7.53)	26.91	76.64	100.50	65.68	(0.11)
20	175.36	180.56	(5.20)	-3%	90.44	(118.02)	(93.10)	(41.17)	(5.20)	30.77	82.70	107.62	68.59	(0.08)
21	183.28	193.05	(9.76)	-5%	87.88	(115.72)	(92.32)	(43.55)	(9.76)	24.02	72.79	96.20	64.42	(0.15)
22	224.21	220.69	3.52	2%	84.89	(128.88)	(99.63)	(38.69)	3.52	45.73	106.67	135.91	80.49	0.04
23	247.43	234.46	12.97	5%	82.94	(161.08)	(122.64)	(42.52)	12.97	68.46	148.58	187.02	105.82	0.12
24	257.34	250.82	6.52	3%	81.41	(183.05)	(141.18)	(53.92)	6.52	66.96	154.22	196.09	115.25	0.06
Daily	**Reference load kWh**	**Estimated kWh**	**Load kWh Δ**	**% Chang**	**Avg F**	**Uncertainty Adjusted Impact - Percentiles 5th**	**10th**	**30th**	**50th**	**70th**	**90th**	**95th**	**Std Err**	**T-statistic**
Overall	6,673.18	6,624.60	48.58	1%	85	(97.19)	(64.99)	2.11	48.58	95.05	162.15	194.35	88.62	0.55
Peak Hours	820.59	847.26	(26.66)	-3%	94	(155.35)	(126.92)	(67.69)	(26.66)	14.36	73.60	102.02	78.23	(0.34)

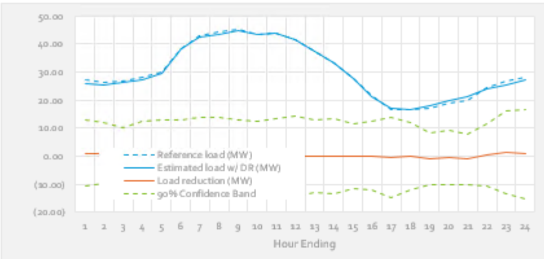
Figure 16: Aggregate Ex Post Impacts on August 18, 2020

Table 1: Menu options

Program	RTP
Reporting Level	Aggregate
Customer Segment	All
Subcategory	All Customers
Ex Post Daytype	Monthly Peak Day
Month	August

Table 2: Event day information

Total sites	109
Daily maximum temperature	101.2
Peak Period (4pm-9pm) Impact (MW)	-0.6
Peak Period (4pm-9pm) Impact (%)	-3.2%
Date	August 18, 2020
RTP Daytype	Moderate Summer Weekday



Hour ending	Reference load (MW)	Estimated load w/ DR (MW)	Load reduction (MW)	% Load reduct	Avg temp (F, site	Uncertainty adjusted impact - Percentiles 5th	10th	30th	50th	70th	90th	95th	Std. error	T-statistic
1	27.13	26.04	1.09	4%	79.23	(14.15)	(10.78)	(3.77)	1.09	5.94	12.96	16.32	9.26	0.12
2	26.50	25.47	1.02	4%	78.24	(12.92)	(9.84)	(3.42)	1.02	5.47	11.89	14.97	8.48	0.12
3	26.92	26.40	0.53	2%	77.52	(11.85)	(9.12)	(3.42)	0.53	4.47	10.17	12.90	7.52	0.07
4	27.95	27.13	0.82	3%	76.69	(14.05)	(10.76)	(3.92)	0.82	5.56	12.40	15.68	9.04	0.09
5	30.09	29.67	0.42	1%	75.65	(15.63)	(12.09)	(4.70)	0.42	5.54	12.93	16.48	9.76	0.04
6	38.30	38.41	(0.11)	0%	75.00	(17.12)	(13.36)	(5.53)	(0.11)	5.32	13.15	16.90	10.34	(0.01)
7	43.15	42.43	0.71	2%	74.73	(16.31)	(12.55)	(4.71)	0.71	6.14	13.98	17.74	10.35	0.07
8	44.16	43.43	0.73	2%	74.50	(16.26)	(12.50)	(4.68)	0.73	6.15	13.97	17.72	10.33	0.07
9	45.31	44.77	0.54	1%	74.49	(15.06)	(11.61)	(4.43)	0.54	5.52	12.70	16.14	9.48	0.06
10	43.59	43.52	0.07	0%	76.19	(15.64)	(12.17)	(4.94)	0.07	5.08	12.31	15.77	9.55	0.01
11	44.05	44.09	(0.05)	0%	80.60	(17.28)	(13.47)	(5.54)	(0.05)	5.45	13.38	17.18	10.47	(0.00)
12	41.44	41.54	(0.10)	0%	86.18	(18.61)	(14.52)	(6.00)	(0.10)	5.80	14.32	18.41	11.25	(0.01)
13	37.57	37.60	(0.03)	0%	90.89	(16.40)	(12.78)	(5.24)	(0.03)	5.19	12.73	16.34	9.95	(0.00)
14	33.05	33.12	(0.07)	0%	94.48	(17.44)	(13.61)	(5.61)	(0.07)	5.47	13.47	17.30	10.56	(0.01)
15	27.78	27.83	(0.05)	0%	98.55	(14.64)	(11.42)	(4.70)	(0.05)	4.60	11.32	14.54	8.87	(0.01)
16	21.48	21.33	0.16	1%	100.06	(15.39)	(11.96)	(4.80)	0.16	5.11	12.27	15.71	9.45	0.02
17	16.54	16.97	(0.44)	-3%	101.16	(18.58)	(14.57)	(6.22)	(0.44)	5.35	13.70	17.71	11.03	(0.04)
18	16.76	16.78	(0.02)	0%	97.47	(15.22)	(11.86)	(4.87)	(0.02)	4.83	11.83	15.18	9.24	(0.00)
19	17.05	17.87	(0.82)	-5%	93.49	(12.60)	(9.99)	(4.57)	(0.82)	2.93	8.35	10.95	7.16	(0.11)
20	19.11	19.68	(0.57)	-3%	90.44	(12.86)	(10.15)	(4.49)	(0.57)	3.35	9.01	11.73	7.48	(0.08)
21	19.98	21.04	(1.06)	-5%	87.88	(12.61)	(10.06)	(4.75)	(1.06)	2.62	7.93	10.49	7.02	(0.15)
22	24.44	24.06	0.38	2%	84.89	(14.05)	(10.86)	(4.22)	0.38	4.98	11.63	14.81	8.77	0.04
23	26.97	25.56	1.41	5%	82.94	(17.56)	(13.37)	(4.63)	1.41	7.46	16.20	20.39	11.53	0.12
24	28.05	27.34	0.71	3%	81.41	(19.95)	(15.39)	(5.88)	0.71	7.30	16.81	21.37	12.56	0.06
Daily	**Reference load MWh**	**Estimated MWh**	**Load MWh Δ**	**% Chang**	**Avg F**	**Uncertainty Adjusted Impact - Percentiles 5th**	**10th**	**30th**	**50th**	**70th**	**90th**	**95th**	**Std Err**	**T-statistic**
Overall	727.38	722.08	5.30	1%	85	(140.47)	(108.28)	(41.18)	5.30	51.77	118.87	151.07	88.62	0.06
Peak Hours	89.44	92.35	(2.91)	-3%	94	(131.59)	(103.17)	(43.93)	(2.91)	38.12	97.35	125.78	78.23	(0.04)

To get a better sense of the average program impacts across day types, the average PY2020 ex post peak period impacts are summarized in Table 14. Ex post impacts are predictably higher on Hot Summer Weekdays, while impacts decline in Moderate and Mild Summer Weekdays. While there is no statistical difference in consumption between High Cost and Low Cost Winter Weekdays, there is a reduction in consumption during the weekend peak on High Cost Weekends compared to Low Cost Weekends.

Table 14: Ex Post Peak Period Impacts by Average Day Type

LCA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI	% Impact	
Hot Summer Weekday	112	328.40	272.20	56.20	-32.26 - 144.65	17.1	6.29
Moderate Summer Weekday	112	359.61	391.34	-31.74	-120.19 - 56.72	-8.8	-3.55
Mild Summer Weekday	112	353.29	398.30	-45.01	-133.47 - 43.44	-12.7	-5.04
High Cost Winter Weekday	112	448.78	454.07	-5.29	-93.74 - 83.17	-1.2	-0.59
Low Cost Winter Weekday	113	457.61	466.35	-8.74	-97.19 - 79.72	-1.9	-0.99
High Cost Weekend	116	321.01	268.68	52.33	-36.13 - 140.78	16.3	6.07
Low Cost Weekend	116	344.36	341.26	3.10	-85.36 - 91.55	0.9	0.36

While the program can deliver up to 6.3MW during peak periods, performance on individual days will vary. Of particular interest is how the program performed on several key days in August of 2020. August 14th and 15th were days of extreme grid strain, culminating in rotating outages at the direction of the California ISO. August 18th was the system peak day. As discussed above, these days were not classified as Hot Summer Weekdays, and therefore did not provide statistically significant impacts, except on Saturday, August 15th, where 1.82MW of load was reduced during the peak period. Table 15 contains more details of load reduction on these key dates.

Table 15: Ex Post Peak Period Impacts on Key PY2020 Dates

Date	Day Type	Average Customer (kW)					
		# Dis-patched	Ref. Load	Impact	95% CI	% Impact	Agg. Impact (MW)
Aug 14, 2020	Moderate Summer Weekday	109	163.55	-5.33	-20.23 - 9.56	-3.3	-0.58
Aug 15, 2020	High Cost Weekend	109	132.11	16.73	2.12 - 31.33	12.7	1.82
Aug 18, 2020	Moderate Summer Weekday	109	164.12	-5.33	-20.42 - 9.75	-3.2	-0.58

4.2 RESULTS BY CATEGORY

In the following tables, values are reported for key RTP customer segments on the average Hot Summer Weekday. As discussed above, the system peak day was not a Hot Summer Weekday, so impacts were minimal on that day. The following tables instead show the ex post results averaged across all the days in the 2020 that were 'Hot Summer Weekdays' to better summarize program performance. It's important to note that these results will not match the load impact tables, as the load impact tables show only an example 'monthly peak day' and 'average weekday' on a given day per month. This change was done for several reasons:

1. It's a more representative summary of the ex post performance over the prior year
2. The individual ex post days are now more noisy on a day-to-day basis with the inclusion of synthetic controls. The synthetic controls provide more estimation precision at the average event day level – especially with the effects of COVID, but can obscure the day-to-day effects of the program.
3. It helps facilitate the comparison to ex ante impacts, since ex ante relies on all of the ex post data rather than just snapshots of individual days

The majority of impacts came from the LA Basin LCA, which delivered 5.7MW of the 6.3MW from 4pm-9pm on the average Hot Summer Weekday. This was primarily due to the large customer size and price responsiveness of these customers. Average reference loads were nearly 350kW and peak period impacts were nearly 19%. The other LCAs provided significantly less per-customer and aggregate impacts.

Table 16: Ex Post Impacts by LCA on Average Hot Summer Weekday

LCA	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
Outside LA Basin	6	[redacted]					
Big Creek/Ventura	19						
LA Basin	87	347.34	281.85	65.49	-48.46 - 179.44	18.9	5.70
All Customers	112	328.40	272.20	56.20	-32.26 - 144.65	17.1	6.29

In the zones affected by the San Onofre Nuclear Generating Station (SONGS), customers delivered 4.59MW of load reduction during the full event hours. This was driven primarily by customers in [redacted] of the total load shed despite representing just 24% of the total population.

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Table 17: Ex Post Impacts by Zone on Average Hot Summer Weekday

Size	# Enrolled	Average Customer (kW) Ref. Load	Obs. Load	Impact	95% CI	% Impact	Agg. Impact (MW)
South Orange County	13	[redacted]					
South of Lugo	27						
Remainder of System	72	218.49	194.88	23.61	-4.45 - 51.68	10.8	1.70
All Customers	112	328.40	272.20	56.20	-32.26 - 144.65	17.1	6.29

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 17%) than the smaller customers, essentially providing all the aggregate impacts associated with this day.

Table 18: Ex Post Impacts by Customer Size on Average Hot Summer Weekday

Size	# Enrolled	Average Customer (kW) Ref. Load	Obs. Load	Impact	95% CI	% Impact	Agg. Impact (MW)
20-200kW	11	[redacted]					
20kW or Lower	16						
Greater than 200kW	85	430.95	356.82	74.13	-43.91 - 192.18	17.2	6.30
All Customers	112	328.40	272.20	56.20	-32.26 - 144.65	17.1	6.29

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

Table 19: Ex Post Impacts by AutoDR Status on Average Hot Summer Weekday

AutoDR Status	# Enrolled	Average Customer (kW) Ref. Load	Obs. Load	Impact	95% CI	% Impact	Agg. Impact (MW)
Yes	11	[redacted]					
No	101						
All Customers	112	328.40	272.20	56.20	-32.26 - 144.65	17.1	6.29

4.3 COMPARISON TO PRIOR YEAR

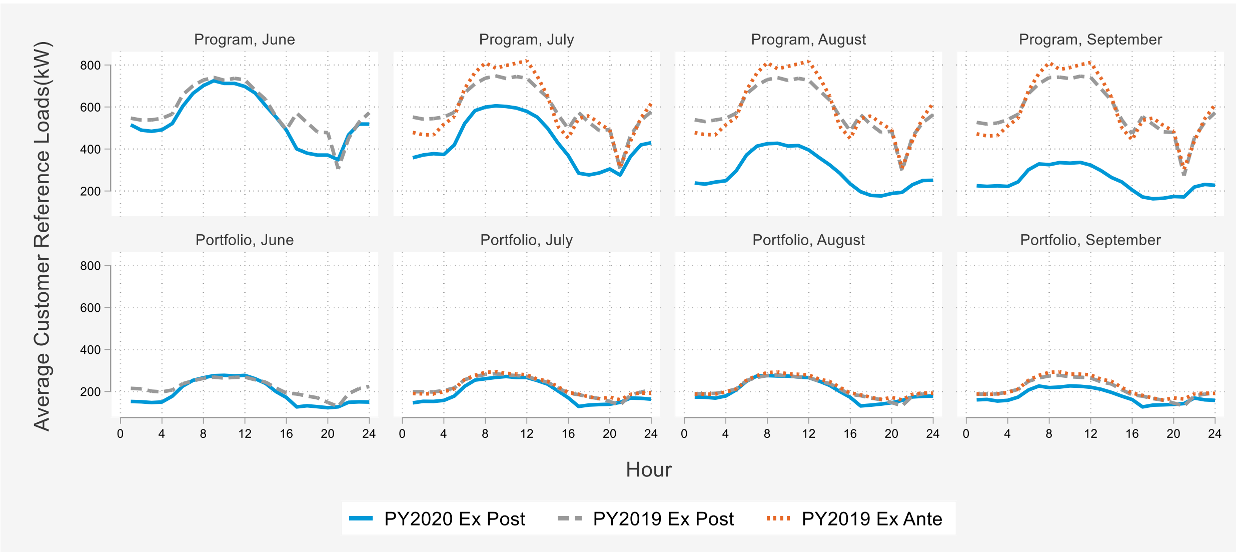
PY2020 represents the first year that customers have been exposed to the new RTP rate for a full year. As a result, the comparisons between PY2020 and PY2019 results are slightly easier to parse. Nevertheless, the impact of the COVID-19 pandemic on industrial customer loads means that changes between last year's results and ex ante forecast and PY2020 ex post results are not unexpected. Table 20 summarizes the details of these comparisons. This table summarizes the average across all days of each month for Hot Summer Weekdays and Moderate Summer Weekdays to capture the distributions of peak period impacts.

Table 20: Comparison of PY2020 to PY2019 Ex Post and Ex Ante Average Customer Reference Loads and Impacts (kW)

Day Type	Year	Type	Method	Portfolio	Average # Customers	June Reference	June Impact	July Reference	July Impact	August Reference	August Impact	September Reference	September Impact
Hot Summer Weekday	PY2020	Ex Post	Event	Portfolio	80	132.2	9.0	142.1	8.6	157.0	8.8	143.4	9.0
				Program	109	411.0	82.8	386.1	82.1	201.3	23.3	185.1	23.6
			Price	Portfolio	80	127.3	5.5	138.1	5.4	142.3	5.1	136.0	5.3
				Program	109	374.3	56.7	285.7	57.7	186.9	17.8	169.3	18.2
	PY2019	Ex Post	Price	Portfolio	71	162.7	13.2	162.9	16.4	158.0	15.7	155.9	15.4
				Program	100	472.0	140.7	477.2	147.9	467.7	142.8	461.1	140.5
		Ex Ante	Price	Portfolio	79			172.3	-0.2	170.3	-2.7	168.8	-5.0
				Program	101			485.5	216.7	485.0	214.3	477.0	207.7
Moderate Summer Weekday	PY2020	Ex Post	Event	Portfolio	79	134.5	-3.0	137.6	-3.0	153.9	-2.9	156.6	-2.8
				Program	109	391.1	-3.4	399.3	-3.4	273.9	-3.6	206.9	-3.6
			Price	Portfolio	79	134.1	-4.6	133.7	-4.6	139.2	-4.7	154.1	-4.8
				Program	109	381.3	-32.6	344.2	-31.4	252.9	-14.6	203.7	-5.3
	PY2019	Ex Post	Price	Portfolio	71	162.7	-8.7	161.0	-4.6	159.3	-4.5	152.3	-5.2
				Program	100	472.0	5.0	473.7	9.8	470.4	7.3	452.3	4.1
		Ex Ante	Price	Portfolio	85	176.4	9.7						
				Program	102	482.6	44.7						

The main difference between PY2019 and PY2020 results is the impact of COVID-19. In particular, one large customer changed their operating schedule during the summer of 2020, and consequently reductions can be seen in the reference loads associated with the aggregate program. Figure 17 shows the comparison on Hot Summer Weekdays. In June, for example, loads for PY2019 and PY2020 ex post are very similar; however over time the PY2020 ex post reference loads diminish. In the portfolio case, which excludes dually enrolled customers, the ex post and ex ante values are quite similar.

Figure 17: Comparison of PY2019 Ex Post and Ex Ante to PY2020 Ex Post



4.4 KEY FINDINGS

RTP delivered approximately 6.3MW of load relief during the 4pm-9pm peak period on the average Hot Summer Day, representing a 17% impact. The impacts in this program reduced over time due to operating schedule changes at key customers and the effects of the COVID-19 pandemic. The largest concentrations of impacts and participants were among large customers, dually enrolled customers, and concentrated in the LA Basin LCA.

5 EX ANTE RESULTS

This section summarizes the results of the ex ante impact estimation process for RTP from 2021 to 2031.

5.1 ENROLLMENT FORECAST

RTP enrollment is expected to decline from the 110 participants enrolled at the end of Summer 2020 to 93 in August of 2024, with an expected loss of four service accounts per year until 2024 when the program stabilizes.

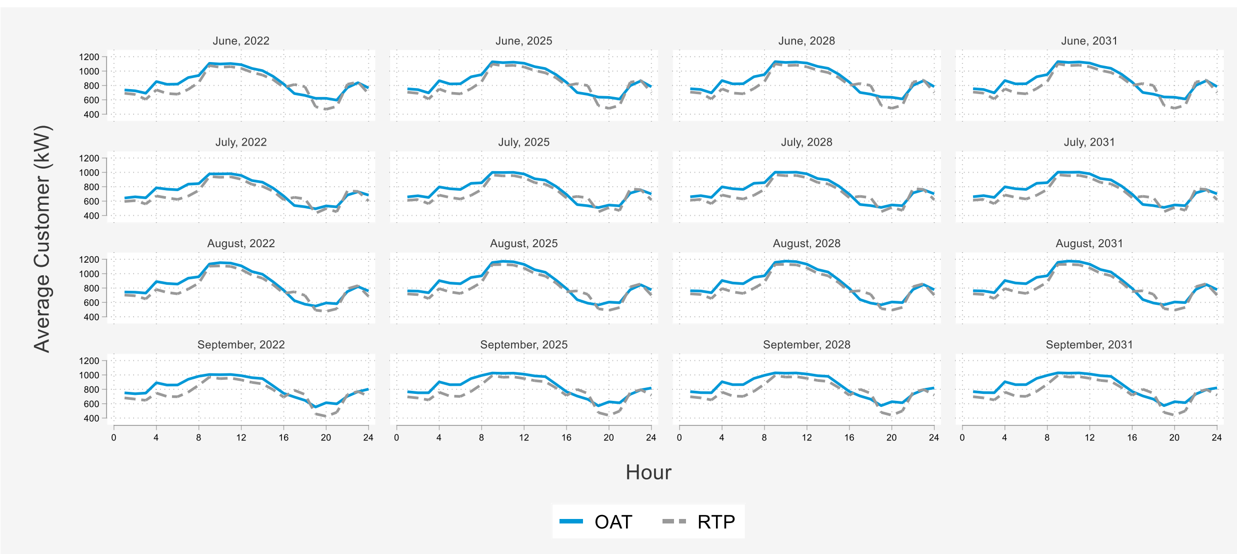
Table 21: RTP Ex Ante Enrollment Forecast

Program/Portfolio	2021	2022	2023	2024	2025	2026	2027-2031
Portfolio	74	71	68	65	65	65	65
Program	105	101	97	93	93	93	93

5.2 OVERALL RESULTS

As in the ex post analysis, the concentration of RTP prices during a subset of the RA hours (4pm-9pm) results in load shifting that happens in the hours before 6pm-9pm on hot summer weekdays. As a result, the models that rely on prices shift consumption to the first hours of the RA window and away from the second half of the window. While this indeed shows that customers are responsive to price, and critically, responsive to price during the hours when the grid experiences the net peak loads, a comparison that looks at impacts across the average RA window will always see diluted impacts as a result. Figure 18 shows this trend by month and for a subset of years in the ex ante forecast horizon. Some impact of COVID-19 persists in the reference and observed loads through the 11 years of the forecast horizon as there is a slight rebound in loads over time.

Figure 18: Average Customer Program Ex Ante Profiles by Year and Month on Hot Summer Days



The RTP program is not expected to produce statistically significant portfolio impacts in ex ante. As discussed above, this is related to two factors: the majority of large customers being enrolled in a separate demand response program such as BIP, and the relative prices of RTP and OAT during the first half of the RA window leading to load shifting. Table 22 contains a summary of the impacts by forecast year. 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 22: RTP Aggregate Portfolio Ex Ante Impacts - August Peak Day (MW)

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2021	-0.02	-0.02	-0.02	-0.02
2022	-0.04	-0.04	-0.04	-0.04
2023	-0.04	-0.04	-0.04	-0.04
2024	-0.04	-0.04	-0.04	-0.04
2025	-0.04	-0.04	-0.04	-0.04
2026	-0.04	-0.04	-0.04	-0.04
2027	-0.04	-0.04	-0.04	-0.04
2028	-0.04	-0.04	-0.04	-0.04
2029	-0.04	-0.04	-0.04	-0.04
2030	-0.04	-0.04	-0.04	-0.04
2031	-0.04	-0.04	-0.04	-0.04

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 23 are the average customer impacts for a monthly peak day. 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 shift the RTP day type customers are subjected to. In those cases, impacts can move significantly.

Table 23: RTP Average Customer Portfolio Ex Ante Impacts - By Monthly Peak Day in 2031 (kW)

Day Type	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
January Peak Day	-18.84	-18.84	-18.84	-18.84
February Peak Day	-18.19	-18.19	-18.19	-18.19
March Peak Day	-5.79	-5.82	-5.79	-5.82
April Peak Day	-5.52	-5.63	-5.52	-5.63
May Peak Day	-5.93	-5.94	-5.93	-5.94
June Peak Day	-16.54	-3.65	-16.54	-3.65
July Peak Day	-7.68	-7.68	-7.68	-7.68
August Peak Day	-0.68	-0.68	-0.68	-0.68
September Peak Day	12.88	12.88	12.88	12.88
October Peak Day	-5.68	-5.68	-5.68	-5.68
November Peak Day	-30.38	-30.38	-18.65	-30.38
December Peak Day	-18.96	-18.96	-18.96	-18.96

The following figures show the results on an August monthly peak day under SCE 1-in-2 conditions at the program and portfolio level.

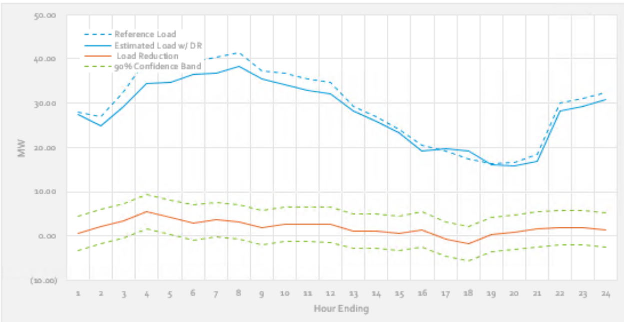
Figure 19: Portfolio Aggregate Ex Ante Impacts for SCE 1-in-2 August Peak Day

Table 1: Menu options

Program	RTP
Type of Result	Aggregate
Category	All
Subcategory	All Customers
Weather Data	SCE
Weather Year	1-in-2
Day Type	Monthly System Peak Day
Month	8
Forecast Year	2021

Table 2: Event day information

On Peak Hours	4pm-9pm
# Enrolled	74
Daily Max Temp	91.9
MW Impact On Peak	0.0
% Impact On Peak	-0.1%
RTP Daytype	Hot Summer Weekday



Hour Ending	Reference Load MW	Estimated Load w/ DR MW	Load Reduction MW	% Load Reduction	Avg Temp, site F	Uncertainty Adjusted Impact - Percentiles 5th	10th	30th	50th	70th	90th	95th	Std Err	T-statistic
1	27.85	27.37	0.48	1.7%	76.7	-4.5	-3.4	-1.1	0.5	2.1	4.4	5.5	3.1	0.16
2	26.94	24.85	2.09	7.8%	75.7	-2.9	-1.8	0.5	2.1	3.7	6.0	7.1	3.1	0.68
3	32.68	29.31	3.38	10.3%	75.0	-1.6	-0.5	1.8	3.4	5.0	7.3	8.4	3.1	1.11
4	39.95	34.55	5.41	13.5%	74.1	0.4	1.5	3.8	5.4	7.0	9.3	10.4	3.1	1.77
5	38.88	34.72	4.16	10.7%	73.5	-0.9	0.3	2.6	4.2	5.8	8.1	9.2	3.1	1.36
6	39.46	36.47	3.00	7.6%	73.0	-2.0	-0.9	1.4	3.0	4.6	6.9	8.0	3.1	0.98
7	40.45	36.83	3.62	9.0%	72.5	-1.4	-0.3	2.0	3.6	5.2	7.5	8.6	3.1	1.19
8	41.31	38.19	3.12	7.5%	72.5	-1.9	-0.8	1.5	3.1	4.7	7.0	8.1	3.1	1.02
9	37.37	35.55	1.82	4.9%	74.4	-3.2	-2.1	0.2	1.8	3.4	5.7	6.8	3.1	0.60
10	36.78	34.16	2.62	7.1%	78.2	-2.4	-1.3	1.0	2.6	4.2	6.5	7.6	3.1	0.86
11	35.54	32.94	2.60	7.3%	82.3	-2.4	-1.3	1.0	2.6	4.2	6.5	7.6	3.1	0.85
12	34.70	32.17	2.53	7.3%	85.9	-2.5	-1.4	0.9	2.5	4.1	6.4	7.6	3.1	0.83
13	29.27	28.25	1.02	3.5%	88.3	-4.0	-2.9	-0.6	1.0	2.6	4.9	6.0	3.1	0.33
14	27.01	26.01	1.00	3.7%	90.5	-4.0	-2.9	-0.6	1.0	2.6	4.9	6.0	3.1	0.33
15	24.04	23.39	0.65	2.7%	91.9	-4.4	-3.3	-1.0	0.6	2.3	4.6	5.7	3.1	0.21
16	20.56	19.09	1.46	7.1%	91.7	-3.6	-2.5	-0.1	1.5	3.1	5.4	6.5	3.1	0.48
17	19.11	19.81	(0.71)	-3.7%	91.0	-5.7	-4.6	-2.3	-0.7	0.9	3.2	4.3	3.0	(0.23)
18	17.29	19.11	(1.82)	-10.5%	89.5	-6.8	-5.7	-3.4	-1.8	-0.2	2.1	3.2	3.1	(0.60)
19	16.41	16.18	0.23	1.4%	88.1	-4.8	-3.7	-1.4	0.2	1.8	4.1	5.2	3.0	0.08
20	16.61	15.88	0.73	4.4%	86.4	-4.3	-3.2	-0.9	0.7	2.3	4.6	5.7	3.0	0.24
21	18.47	16.98	1.49	8.1%	82.9	-3.6	-2.5	-0.1	1.5	3.1	5.5	6.6	3.1	0.48
22	30.02	28.19	1.83	6.1%	79.8	-3.2	-2.1	0.2	1.8	3.4	5.8	6.9	3.1	0.60
23	31.05	29.19	1.85	6.0%	77.8	-3.2	-2.1	0.3	1.9	3.5	5.8	6.9	3.1	0.61
24	32.24	30.81	1.44	4.5%	76.4	-3.6	-2.5	-0.2	1.4	3.0	5.3	6.5	3.1	0.47

Daily	Reference Load MWh	Estimated Load w/ DR MWh	Load Reduction MWh Δ	% Change	Avg Temp, site F	Uncertainty Adjusted Impact - Percentiles 5th	10th	30th	50th	70th	90th	95th	Std Err	T-statistic
Overall	713.99	670.00	43.99	6.2%	81	-23.9	-8.9	22.4	44.0	65.6	96.9	111.8	41.26	1.07
Peak Hours	87.88	87.96	(0.08)	-0.1%	88	-67.9	-52.9	-21.7	-0.1	21.5	52.8	67.7	41.24	(0.00)

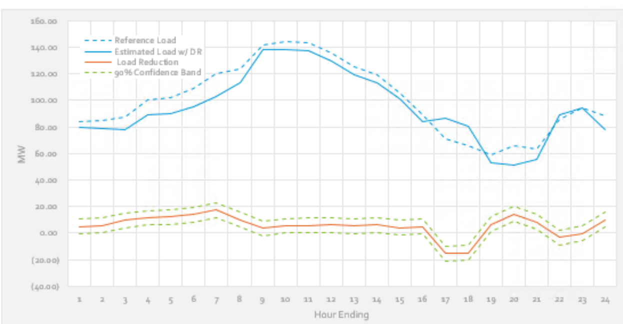
Figure 20: Program Aggregate Ex Ante Impacts for SCE 1-in-2 August Peak Day

Table 1: Menu options

Program	RTP
Type of Result	Aggregate
Category	All
Subcategory	All Customers
Weather Data	SCE
Weather Year	1-in-2
Day Type	Monthly System Peak Day
Month	8
Forecast Year	2021

Table 2: Event day information

On Peak Hours	4pm-9pm
# Enrolled	105
Daily Max Temp	92.3
MW Impact On Peak	-0.1
% Impact On Peak	-0.2%
RTP Daytype	Hot Summer Weekday



Hour Ending	Reference Load MW	Estimated Load w/ DR MW	Load Reduction MW	% Load Reduction	Avg Temp, site F	Uncertainty Adjusted Impact - Percentiles 5th	10th	30th	50th	70th	90th	95th	Std Err	T-statistic
1	84.32	79.29	5.03	6.0%	76.9	-2.1	-0.5	2.8	5.0	7.3	10.6	12.2	4.3	1.16
2	85.01	79.13	5.88	6.9%	75.9	-1.2	0.3	3.6	5.9	8.2	11.4	13.0	4.3	1.36
3	87.64	78.05	9.60	11.0%	75.2	2.5	4.1	7.3	9.6	11.9	15.1	16.7	4.3	2.22
4	100.37	88.81	11.56	11.5%	74.3	4.4	6.0	9.3	11.6	13.8	17.1	18.7	4.3	2.67
5	102.06	89.94	12.13	11.9%	73.7	5.0	6.6	9.9	12.1	14.4	17.7	19.2	4.3	2.80
6	108.93	95.11	13.82	12.7%	73.2	6.7	8.3	11.6	13.8	16.1	19.4	20.9	4.3	3.19
7	120.28	103.01	17.27	14.4%	72.7	10.1	11.7	15.0	17.3	19.5	22.8	24.4	4.3	3.99
8	123.45	113.16	10.29	8.3%	72.8	3.2	4.7	8.0	10.3	12.6	15.8	17.4	4.3	2.38
9	142.08	138.52	3.55	2.5%	74.8	-3.6	-2.0	1.3	3.6	5.8	9.1	10.7	4.3	0.82
10	144.19	138.66	5.53	3.8%	78.6	-1.6	0.0	3.3	5.5	7.8	11.1	12.7	4.3	1.28
11	143.21	137.49	5.73	4.0%	82.7	-1.4	0.2	3.5	5.7	8.0	11.3	12.9	4.3	1.32
12	135.88	129.66	6.22	4.6%	86.2	-0.9	0.7	3.9	6.2	8.5	11.8	13.3	4.3	1.43
13	124.93	119.43	5.50	4.4%	88.7	-1.6	-0.1	3.2	5.5	7.8	11.1	12.6	4.3	1.27
14	119.45	113.07	6.38	5.3%	90.9	-0.7	0.8	4.1	6.4	8.7	11.9	13.5	4.3	1.47
15	105.16	101.09	4.07	3.9%	92.3	-3.1	-1.5	1.8	4.1	6.3	9.6	11.2	4.3	0.94
16	88.87	83.96	4.91	5.5%	92.2	-2.2	-0.6	2.6	4.9	7.2	10.5	12.0	4.3	1.13
17	70.98	86.23	(15.25)	-21.5%	91.4	-22.4	-20.8	-17.5	-15.2	-13.0	-9.7	-8.1	4.3	(3.53)
18	65.64	80.45	(14.81)	-22.6%	89.9	-21.9	-20.4	-17.1	-14.8	-12.5	-9.3	-7.7	4.3	(3.42)
19	59.33	52.64	6.69	11.3%	88.5	-0.4	1.2	4.4	6.7	9.0	12.2	13.8	4.3	1.55
20	65.88	51.51	14.37	21.8%	86.7	7.3	8.9	12.1	14.4	16.6	19.9	21.4	4.3	3.34
21	63.62	55.32	8.30	13.1%	83.1	1.1	2.7	6.0	8.3	10.6	13.9	15.5	4.4	1.89
22	85.40	88.82	(3.42)	-4.0%	80.0	-10.6	-9.0	-5.7	-3.4	-1.1	2.1	3.7	4.3	(0.79)
23	94.51	94.73	(0.22)	-0.2%	78.0	-7.3	-5.8	-2.5	-0.2	2.1	5.3	6.9	4.3	(0.05)
24	88.37	78.32	10.05	11.4%	76.5	2.9	4.5	7.8	10.0	12.3	15.6	17.2	4.3	2.32

Daily	Reference Load MWh	Estimated Load w/ DR MWh	Load Reduction MWh Δ	% Change	Avg Temp, site F	Uncertainty Adjusted Impact - Percentiles 5th	10th	30th	50th	70th	90th	95th	Std Err	T-statistic
Overall	2,409.58	2,276.40	133.18	5.5%	81	65.3	80.3	111.5	133.2	154.8	186.1	201.0	41.26	3.23
Peak Hours	325.45	326.15	(0.70)	-0.2%	88	-68.5	-53.5	-22.3	-0.7	20.9	52.2	67.1	41.24	(0.02)

5.3 RESULTS BY CATEGORY

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

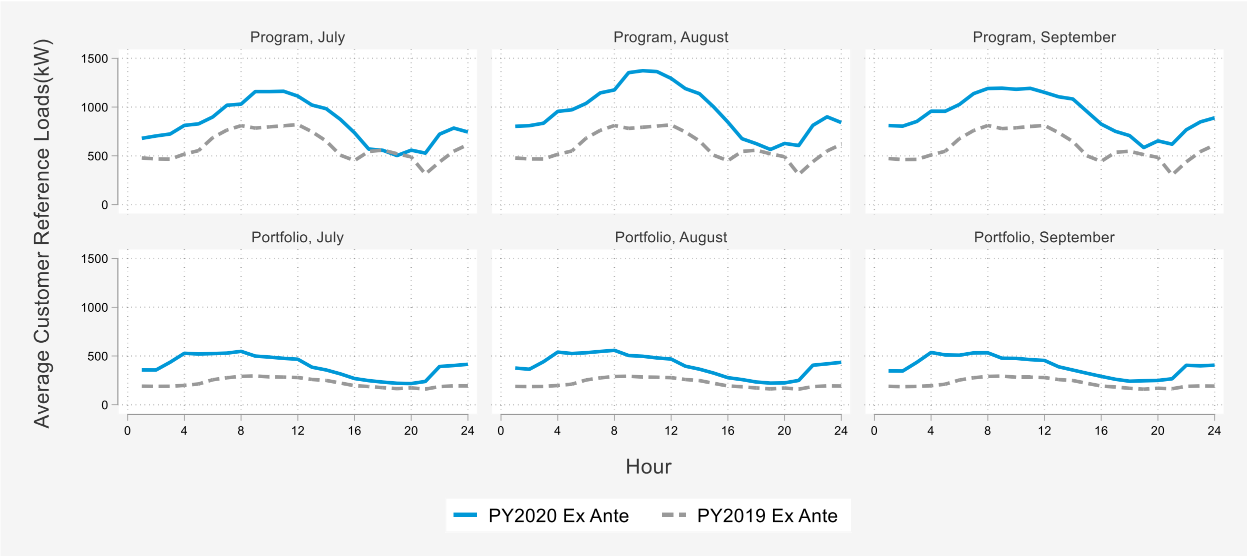
Table 24: RTP Aggregate Portfolio Ex Ante Impacts - Typical Event Day by LCA

LCA	Weather Year	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
Big Creek/ Ventura	CAISO 1-in-10	[redacted]										
	CAISO 1-in-2											
	SCE 1-in-10											
	SCE 1-in-2											
LA Basin	CAISO 1-in-10	-0.1	-0.12	-0.11	-0.11	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12
	CAISO 1-in-2	-0.1	-0.12	-0.11	-0.11	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12
	SCE 1-in-10	-0.1	-0.12	-0.11	-0.11	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12
	SCE 1-in-2	-0.1	-0.12	-0.11	-0.11	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12
Outside LA Basin	CAISO 1-in-10	[redacted]										
	CAISO 1-in-2											
	SCE 1-in-10											
	SCE 1-in-2											

5.4 COMPARISON TO PRIOR YEAR

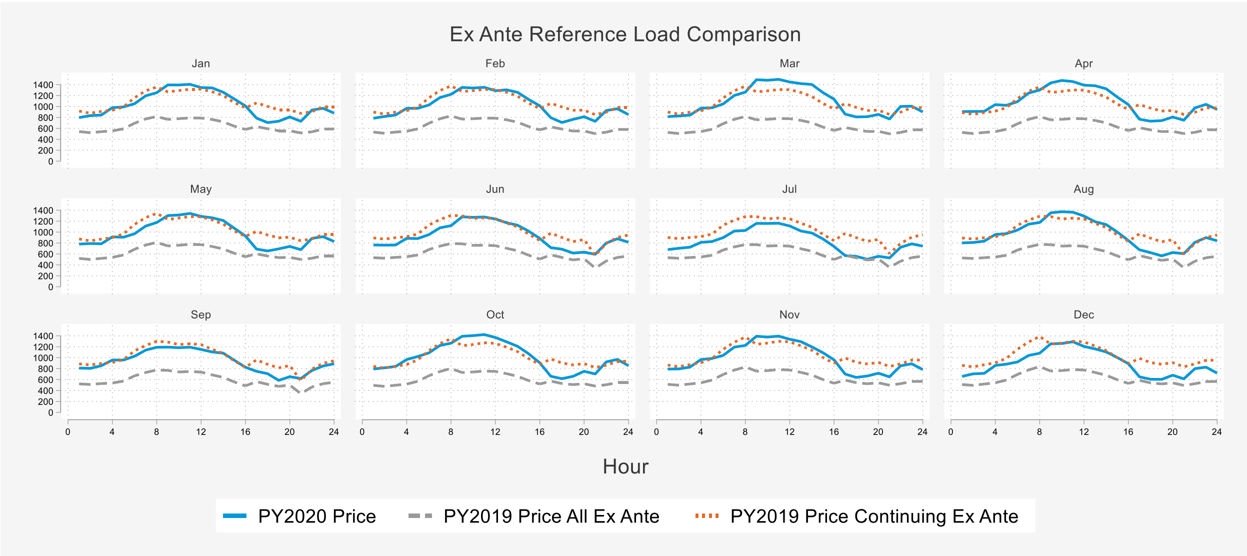
As with the ex post analysis, comparisons between the PY2018 and PY2019 results are challenging due to the extent that the patterns of large customers on any given year can dominate the results. In 2020, of course, all customers were impacted by the effects of the COVID-19 pandemic on their operations as well. In general, ex ante impacts in PY2020 were lower than PY2019 despite reference loads being the same or higher. This effect is diluted by the price signal discussion referenced above, where customers must now focus their load reductions on Hot Summer Weekdays between 6pm and 9pm specifically. As last summer was the first time for RTP participants to experience this new rate regime, they may have adjusted their schedules to more deeply target those specific hours instead of the broader peak with which they were historically billed.

Figure 21: Portfolio Average Ex Ante Reference Loads on Hot Summer Weekdays



The difference in average customer size between PY2019 and PY2020 is attributable to two factors: the effects of COVID-19 on reference loads in PY2020 and the mix of customers enrolled in RTP over the forecast period. Figure 22 shows the average customer reference load between PY2019 and PY2020 for three groups: PY2020 customers, PY2019 customers and PY2019 reference loads for customers who remain on the program in PY2020. The customers who remained on the program from 2019 to 2020 are larger, on average, than customers who left the program prior to September of 2020.

Figure 22: Comparison of PY2020 and PY2019 Ex Ante Reference Loads



6 DISCUSSION

The RTP program can provide a small but measurable amount of demand response impacts during the 6pm-9pm period on Hot Summer Weekdays, when prices relative to the otherwise applicable tariff are high. The program has many customers who are dually enrolled in other demand response programs, making attribution of impacts challenging. Similarly, the program is dominated by several large industrial accounts that provide the majority of the load shed for the program.

As a result, portfolio impacts averaged across the RA window tend to be small. The effects of the COVID-19 pandemic on customers was substantial, and the effect thereof is expected to persist over the 11 years of the forecast horizon.

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? Alternatively, 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 25. 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 25: 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 23 illustrates the process.

Figure 23: Model Selection and Validation

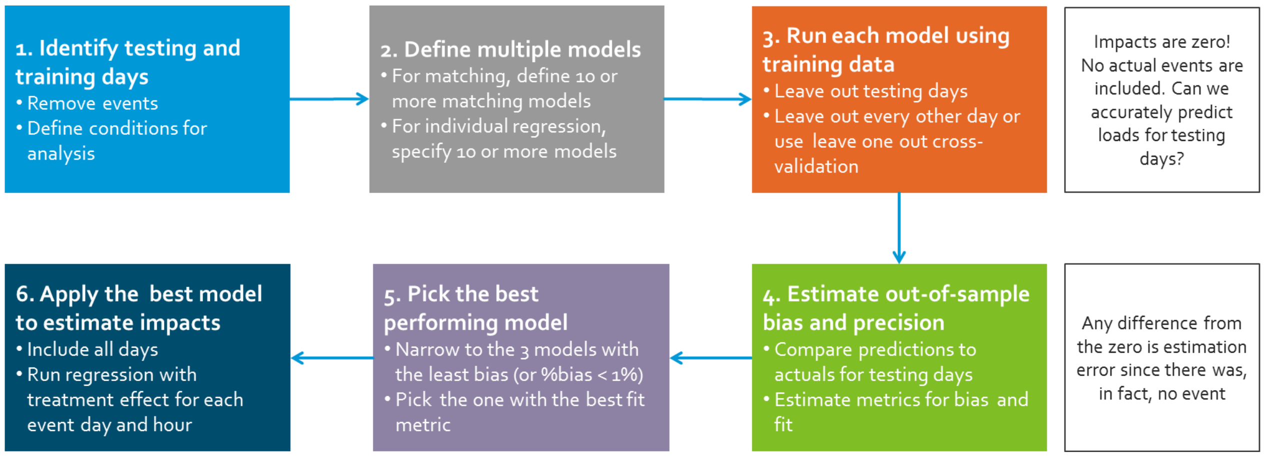


Table 26 summarizes the metrics for bias and precision we employ. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error describes the relative magnitude and direction of the bias. A negative value indicates a tendency 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 26: 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 27 and

Table 28 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. The results of the out of sample fit metrics are listed below.

Table 27: Best Model Out of Sample Fit by Rate Family

Rate	Observed Usage	Avg Error	% Bias	cvRMSE
TOU-8	505.5	4.7	0.9	141.2
TOU-8-S	[redacted]	[redacted]	[redacted]	[redacted]
TOU-GS1	0.7	0	-0.5	52.8
TOU-GS2	[redacted]	[redacted]	[redacted]	[redacted]
TOU-GS3	[redacted]	[redacted]	[redacted]	[redacted]
TOU-PA-2	[redacted]	[redacted]	[redacted]	[redacted]
TOU-PA-3	[redacted]	[redacted]	[redacted]	[redacted]

Table 28: All Tested Models Out of Sample Fit

Model	Control Included	Day Type Adder	Average Usage	Average Error	% Bias	cvRMSE
1	All	Day type & Month	344.8	-10.4	-3	226.5
1	All	DOW & Month	344.8	-10.2	-2.9	237.6
1	All	DOW, Month, & COVID	344.8	-20	-5.8	253.5
1	Industry	Day type & Month	344.8	-7.4	-2.1	199.9
1	Industry	DOW & Month	344.8	-9	-2.6	216.8
1	Industry	DOW, Month, & COVID	344.8	-14	-4.1	225.3
1	None	Day type & Month	344.8	0.9	0.2	199.1
1	None	DOW & Month	344.8	3.6	1.1	214.8
1	None	DOW, Month, & COVID	344.8	-19.8	-5.7	236.4
1	Rate	Day type & Month	344.8	-13.4	-3.9	228.5
1	Rate	DOW & Month	344.8	-13.6	-3.9	236.1
1	Rate	DOW, Month, & COVID	344.8	-20.4	-5.9	253
2	All	Day type & Month	344.8	-10.2	-3	225.4
2	All	DOW & Month	344.8	-11.8	-3.4	241.6
2	All	DOW, Month, & COVID	344.8	-20.4	-5.9	250
2	Industry	Day type & Month	344.8	-5.7	-1.7	194.9
2	Industry	DOW & Month	344.8	-9.2	-2.7	215.1
2	Industry	DOW, Month, & COVID	344.8	-13.2	-3.8	219.3
2	None	Day type & Month	344.8	4.5	1.3	193.8
2	None	DOW & Month	344.8	5.2	1.5	214.2
2	None	DOW, Month, & COVID	344.8	-20.7	-6	233.8
2	Rate	Day type & Month	344.8	-13.6	-3.9	228.3
2	Rate	DOW & Month	344.8	-15.2	-4.4	239.7

Model	Control Included	Day Type Adder	Average Usage	Average Error	% Bias	cvRMSE
2	Rate	DOW, Month, & COVID	344.8	-20.8	-6	249.7
3	All	Day type & Month	344.8	-18.2	-5.3	248.6
3	All	DOW & Month	344.8	-20.5	-5.9	268.1
3	All	DOW, Month, & COVID	344.8	-28.5	-8.3	273.2
3	Industry	Day type & Month	344.8	-11.8	-3.4	209.2
3	Industry	DOW & Month	344.8	-15.8	-4.6	234.1
3	Industry	DOW, Month, & COVID	344.8	-18.5	-5.4	233.4
3	None	Day type & Month	344.8	0	0	206.9
3	None	DOW & Month	344.8	0	0	229.9
3	None	DOW, Month, & COVID	344.8	-26.4	-7.6	250.9
3	Rate	Day type & Month	344.8	-20.9	-6.1	251.7
3	Rate	DOW & Month	344.8	-23.7	-6.9	268.1
3	Rate	DOW, Month, & COVID	344.8	-27.8	-8.1	272.1
4	All	Day type & Month	344.8	-12.3	-3.6	237
4	All	DOW & Month	344.8	-11.5	-3.3	245.4
4	All	DOW, Month, & COVID	344.8	-24.2	-7	263.8
4	Industry	Day type & Month	344.8	-9.7	-2.8	206.7
4	Industry	DOW & Month	344.8	-11.7	-3.4	221.8
4	Industry	DOW, Month, & COVID	344.8	-15.8	-4.6	229.6
4	None	Day type & Month	344.8	10.3	3	192.9
4	None	DOW & Month	344.8	13.2	3.8	206.8
4	None	DOW, Month, & COVID	344.8	-19.8	-5.7	238.7
4	Rate	Day type & Month	344.8	-16	-4.7	241.6
4	Rate	DOW & Month	344.8	-16.5	-4.8	249.5
4	Rate	DOW, Month, & COVID	344.8	-24.1	-7	263.9
5	All	Day type & Month	344.8	6.3	1.8	186.2
5	All	DOW & Month	344.8	4.5	1.3	205.1
5	All	DOW, Month, & COVID	344.8	-7.1	-2.1	210.1
5	Industry	Day type & Month	344.8	6.1	1.8	167.7
5	Industry	DOW & Month	344.8	3.7	1.1	187.2
5	Industry	DOW, Month, & COVID	344.8	-3.8	-1.1	193.2
5	None	Day type & Month	344.8	19.4	5.6	165.6
5	None	DOW & Month	344.8	20	5.8	187.9
5	None	DOW, Month, & COVID	344.8	-10.2	-3	200
5	Rate	Day type & Month	344.8	2.6	0.7	188.5
5	Rate	DOW & Month	344.8	0.9	0.3	202.4
5	Rate	DOW, Month, & COVID	344.8	-8.1	-2.4	210.5

8 APPENDIX: RESULTS FOR EVENT-BASED MODEL

The SCE evaluation and program staff were interested in testing an alternate specification for this year's evaluation in conjunction with the standard price models. In this version, the higher price RTP day types would be treated as an event, and their impacts modeled with an event indicator and without price signals. This model would essentially treat Mild Summer Weekdays, Low Cost Winter Weekdays, and Low Cost Weekends as the baseline performance of these customers, with impacts set to zero. Any deviation from these base profiles on Moderate Summer Weekdays, Hot Summer Weekdays, High Cost Winter Weekdays and High Cost Weekends would be impacts associated with the program.

This approach does not measure the impact of being on an RTP rate compared to the OAT rate. Instead, it measures the amount of load shed associated with the high price RTP day types, relative to the low price RTP day types. In the following tables and figures, we report the results of the evaluation as if it had been completed using this alternate framework.

Ex Post Modeling

Figure 24: Raw Participant Loads on Proxy Days

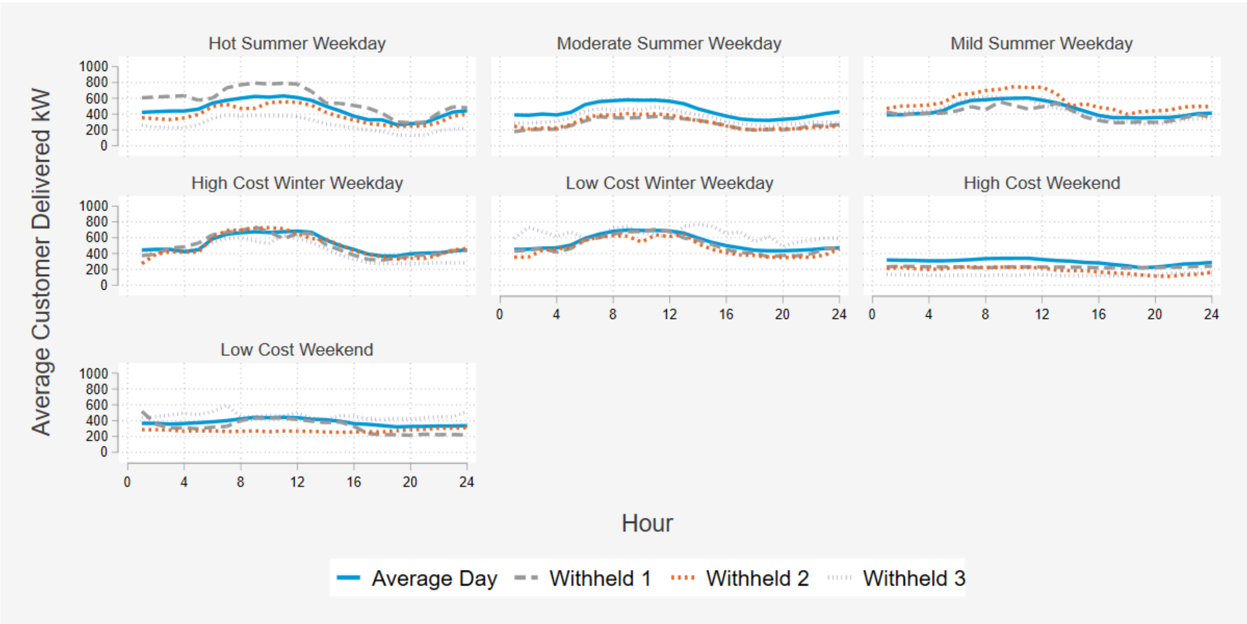


Figure 25: Event Model: Ex Post Out of Sample Model Results

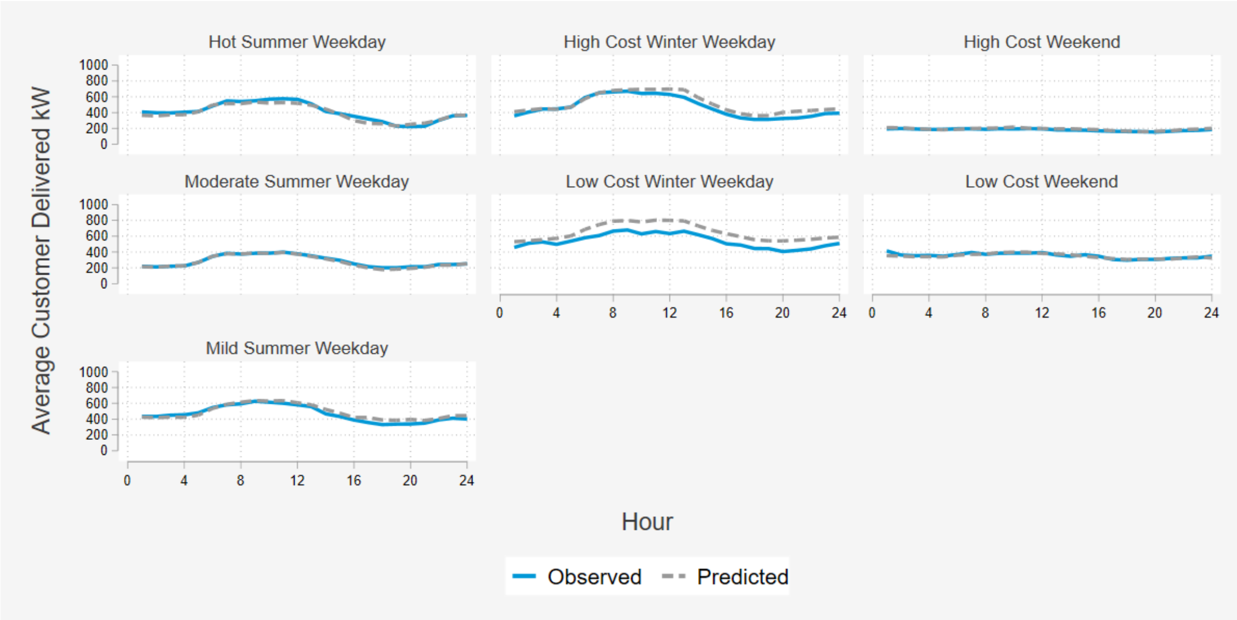


Figure 26: Event Model OAT Peak Hours vs RTP Peak Hours

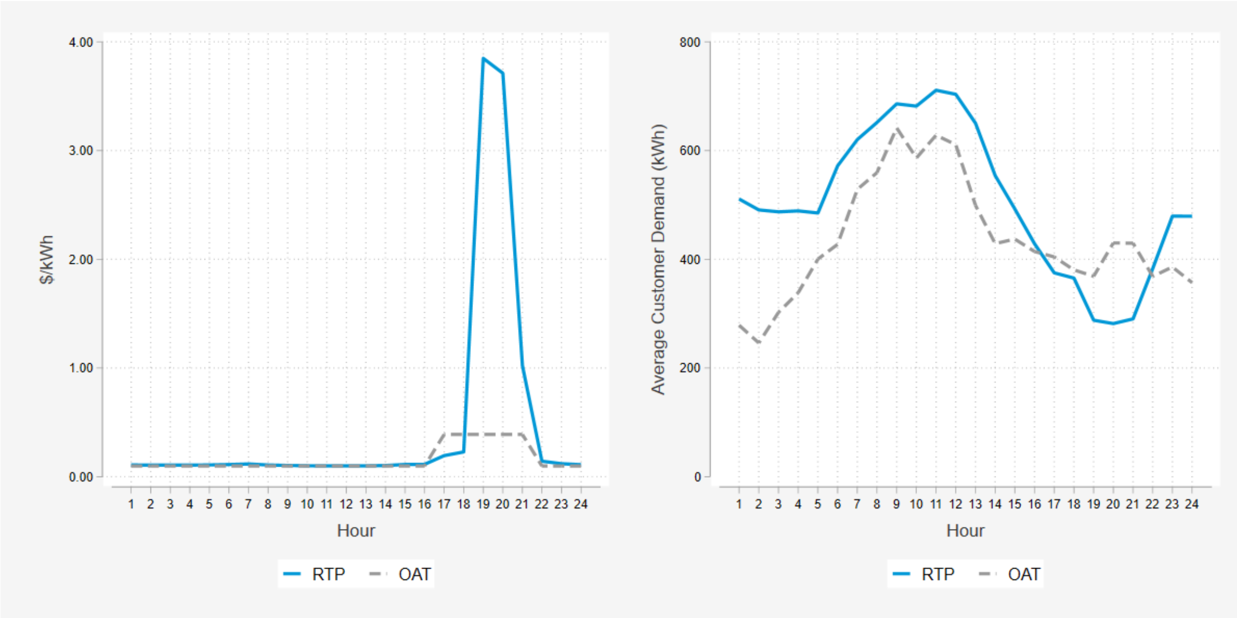


Figure 27: Event Model Moderate Summer Weekday OAT Peak Hours vs RTP Peak Hours

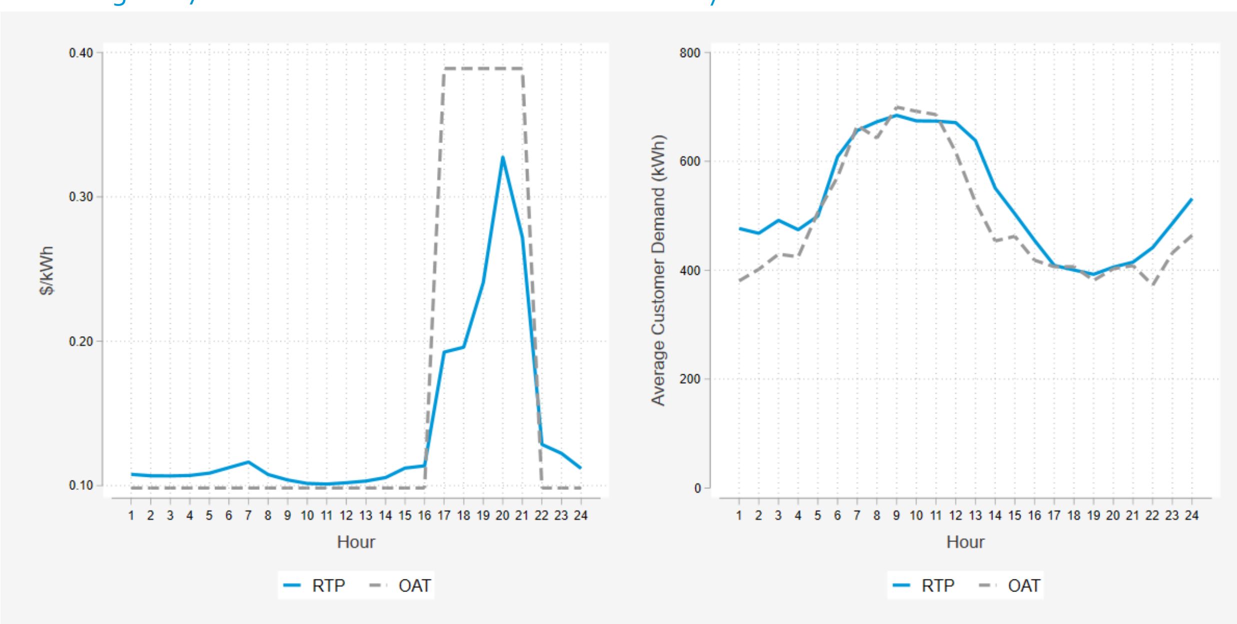


Figure 28: Event Model Average Ex Post Impacts by RTP Day Type

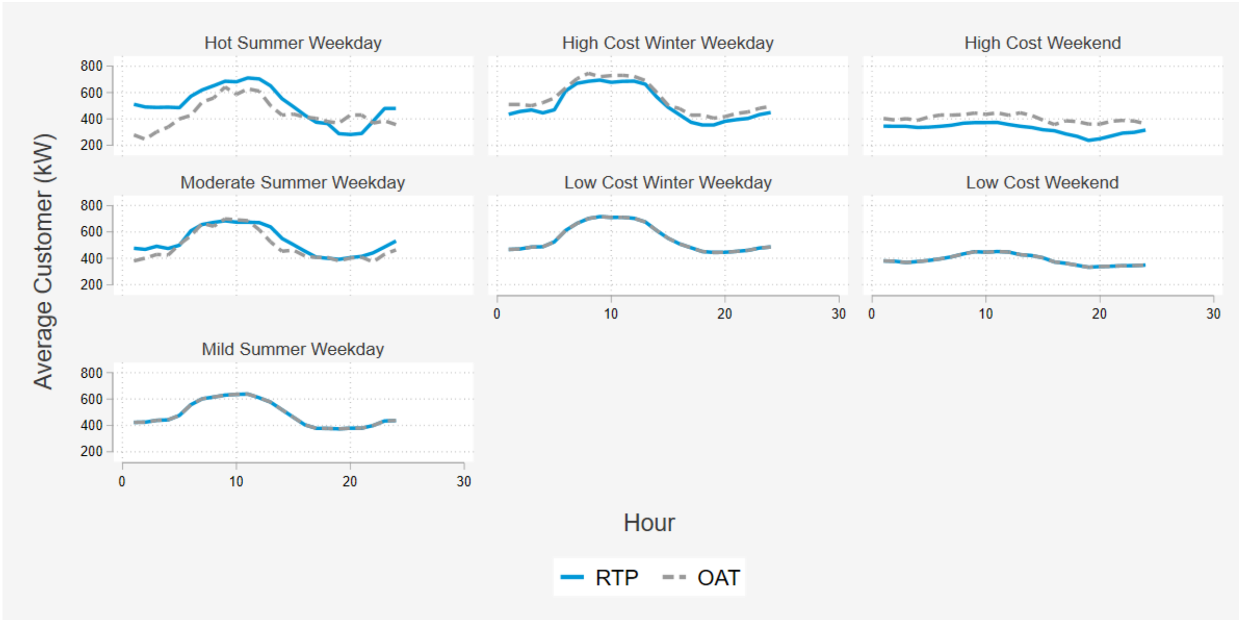


Table 29: Event Model Ex Post Peak Period Impacts by Day Type

Day Type	# Dispatched	Average Customer (kW) Ref.	Obs.	Imp.	95% CI	% Imp.	Agg. Impact (MW)
Hot Summer Weekday	112	391.11	309.60	81.51	80.32 - 82.71	20.8	9.13
Moderate Summer Weekday	112	399.65	402.97	-3.32	-4.51 - -2.12	-0.8	-0.37
Mild Summer Weekday	112	377.42	377.42	0.00	-1.20 - 1.20	0.0	0.00
High Cost Winter Weekday	111	403.28	354.19	49.09	47.89 - 50.29	12.2	5.45
Low Cost Winter Weekday	111	436.94	436.94	0.00	-1.20 - 1.20	0.0	0.00
High Cost Weekend	114	350.19	248.01	102.18	100.98 - 103.37	29.2	11.65
Low Cost Weekend	114	324.50	324.50	0.00	-1.20 - 1.20	0.0	0.00

Table 30: Ex Post Peak Period Impacts on Key PY2020 Dates

Date	Day Type	# Dispatched	Average Customer (kW) Reference	Impact	95% CI	% Impact	Agg. Impact (MW)
Aug 14, 2020	Moderate Summer Weekday	109	169.73	-3.73	-11.82 - 4.35	-2.2	-0.41
Aug 15, 2020	High Cost Weekend	109	140.37	14.20	0.40 - 28.01	10.1	1.55
Aug 18, 2020	Moderate Summer Weekday	109	196.61	-3.73	-11.82 - 4.35	-1.9	-0.41

Table 31: Event Model Ex Post Peak Day Peak Period Impacts by LCA

LCA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Outside LA Basin	6	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Big Creek/Ventura	19	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
LA Basin	87	422.84	329.35	93.49	90.05 - 96.93	22.1	8.13
All Customers	112	391.11	309.60	81.51	78.84 - 84.18	20.8	9.13

Table 32: Event Model Ex Post Peak Day Peak Period Impacts by Zone

Zone	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
South Orange County	13	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
South of Lugo	27	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Remainder of System	72	231.01	198.57	32.43	31.59 - 33.28	14.0	2.34
All Customers	112	391.11	309.60	81.51	78.84 - 84.18	20.8	9.13

Table 33: Event Model Ex Post Peak Day Peak Period Impacts by Customer Size

Size	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
20-200kW	11	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
20kW or Lower	16	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Greater than 200kW	85	513.24	405.95	107.29	103.73 - 110.86	20.9	9.12
All Customers	112	391.11	309.60	81.51	78.84 - 84.18	20.8	9.13

Table 34: Event Model Ex Post Peak Day Peak Period Impacts by AutoDR Status

AutoDR	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Yes	11	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
No	101	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
All Customers	112	391.11	309.60	81.51	78.84 - 84.18	20.8	9.13

Ex Ante Results

Figure 29: Event Model Average Customer Program Ex Ante Profiles by Year and Month on Hot Summer Days

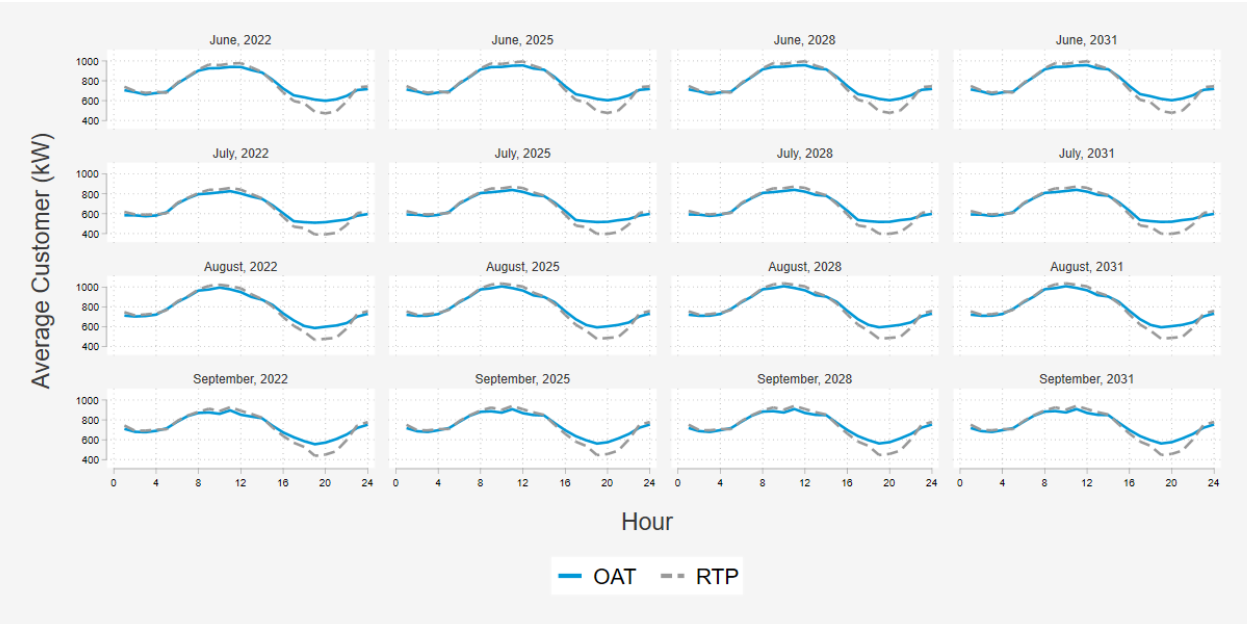


Table 35: Event Model RTP Aggregate Program Ex Ante Impacts - August Peak Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2021	13.29	13.29	13.29	13.29
2022	12.77	12.77	12.77	12.77
2023	12.20	12.20	12.20	12.20
2024	11.66	11.66	11.66	11.66
2025	11.63	11.63	11.63	11.63
2026	11.62	11.62	11.62	11.62
2027	11.61	11.61	11.61	11.61
2028	11.61	11.61	11.61	11.61
2029	11.61	11.61	11.61	11.61
2030	11.60	11.60	11.60	11.60
2031	11.60	11.60	11.60	11.60

Table 36: Event Model RTP Aggregate Portfolio Ex Ante Impacts - August Peak Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2021	0.78	0.78	0.78	0.78
2022	0.74	0.74	0.74	0.74
2023	0.70	0.70	0.70	0.70
2024	0.67	0.67	0.67	0.67
2025	0.67	0.67	0.67	0.67
2026	0.67	0.67	0.67	0.67
2027	0.67	0.67	0.67	0.67
2028	0.67	0.67	0.67	0.67
2029	0.67	0.67	0.67	0.67
2030	0.67	0.67	0.67	0.67
2031	0.67	0.67	0.67	0.67

Table 37: Event Model RTP Average Customer Program Ex Ante Impacts - By Monthly Peak Day

Daytype	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
April	0.00	76.96	0.00	76.96
August	124.77	124.77	124.77	124.77
December	0.00	0.00	0.00	0.00
February	0.00	0.00	0.00	0.00
January	0.00	0.00	0.00	0.00
July	125.76	125.76	125.76	125.76
June	-9.44	127.55	-9.44	127.55
March	0.00	78.68	0.00	78.68
May	0.00	75.93	0.00	75.93
November	79.06	79.06	0.00	79.06
October	79.31	79.31	79.31	79.31
September	124.01	124.01	124.01	124.01

Table 38: Event Model RTP Average Customer Portfolio Ex Ante Impacts - By Monthly Peak Day

Daytype	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
April	0.00	-7.17	0.00	-7.17
August	10.23	10.23	10.23	10.23
December	0.00	0.00	0.00	0.00
February	0.00	0.00	0.00	0.00
January	0.00	0.00	0.00	0.00
July	9.92	9.92	9.92	9.92
June	-4.43	9.91	-4.43	9.91
March	0.00	-7.13	0.00	-7.13
May	0.00	-6.70	0.00	-6.70
November	-7.12	-7.12	0.00	-7.12
October	-6.89	-6.89	-6.89	-6.89
September	10.63	10.63	10.63	10.63

Table 39: Event Model RTP Aggregate Program Ex Ante Impacts - Typical Event Day by LCA

LCA	Weather Year	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
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	12.62	12.19	11.60	11.17	11.16	11.16	11.15	11.15	11.15	11.15	11.15
	CAISO 1-in-2	12.62	12.19	11.60	11.17	11.16	11.16	11.15	11.15	11.15	11.15	11.15
	SCE 1-in-10	12.62	12.19	11.60	11.17	11.16	11.16	11.15	11.15	11.15	11.15	11.15
	SCE 1-in-2	12.62	12.19	11.60	11.17	11.16	11.16	11.15	11.15	11.15	11.15	11.15
Outside LA Basin	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]

Table 40: Event Model RTP Aggregate Portfolio Ex Ante Impacts - Typical Event Day by LCA

LCA	Weather Year	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
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	0.72	0.69	0.65	0.63	0.62	0.62	0.62	0.62	0.62	0.62	0.62
	CAISO 1-in-2	0.72	0.69	0.65	0.63	0.62	0.62	0.62	0.62	0.62	0.62	0.62
	SCE 1-in-10	0.72	0.69	0.65	0.63	0.62	0.62	0.62	0.62	0.62	0.62	0.62
	SCE 1-in-2	0.72	0.69	0.65	0.63	0.62	0.62	0.62	0.62	0.62	0.62	0.62
Outside LA Basin	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]

Figure 30: Event Model Comparison of PY2019 Ex Post and Ex Ante to PY2020 Ex Post